Teachers’ Use of Predictive Learning Analytics: Experiences from The Open University UK

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Abstract

This thesis evaluates the role of predictive learning analytics (PLA) as a teaching tool in higher education. The focus is the Open University’s (OU) Associate Lecturers (ALs). The OU is an online distance learning university in the UK where PLA presented in the form of the Early Alert Indicators (EAI) dashboard which has been available to ALs for over two years. However existing research suggests that it is not well adopted.

The thesis aims to give a better understanding of the reasons for teachers’ resistance to using PLA. It addresses the following research questions: 1) How do existing teacher beliefs relate to Associate Lecturers’ use of PLA? 2) How does (a) knowledge of technology and (b) data literacy relate to Associate Lecturers’ use of PLA? 3) What are Associate Lecturers’ (a) perceptions of the use and usability of PLA and (b) actual use as measured by fine-grained eye-tracking approaches and observation of use?


Using a mixed methods approach, three strands of enquiry were synthesised: Semi-structured interviews with eleven (N=11) participants. Of the 11 participants, six (n=6) participated in a fine-grained observation of EAI use using eye-tracking and retrospective think aloud protocols and five (n=5) participated in a screen-sharing observation and concurrent think aloud protocols.

Findings identified a range of reasons for low engagement with EAI including levels of management support, ethical concerns about use of student data, and evidence of some erroneous interpretations of EAI as identified by the analysis of eye-tracking data and screen-sharing observation.

Conclusion: The support of management, a clear understanding of the ethical basis of EAI and ongoing training are key to the adoption of PLA in online and distance learning in higher education. While theoretical models are useful for understanding technology use, they are limited in their application for PLA and a new model of Technology and Data Acceptance in Education (PLA) is proposed.
Acknowledgements

With grateful thanks to my supervisors Professor Christothea Herodotou and Professor Bart Rienties for their endless support, kindness, and encouragement in getting me across the finish line.

Thank you also to Dr Irina Rets for all her help with supporting me in how to use the eye-tracker.

Finally, to my family for giving me time and believing in me.
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## Acronyms

<table>
<thead>
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<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>AL</td>
<td><strong>Associate Lecturer</strong> <em>(Teachers at the Open University are employed as Associate Lecturers and often on a part time basis with other employment outside of the university)</em>.</td>
</tr>
<tr>
<td>BERA</td>
<td><strong>British Education Research Association</strong>.</td>
</tr>
<tr>
<td>CTAP</td>
<td><strong>Concurrent Think Aloud Protocols</strong> <em>(A method by which thoughts are verbalised whilst performing a task)</em>.</td>
</tr>
<tr>
<td>DTPB</td>
<td><strong>Decomposed Theory of Planned Behaviour</strong> <em>(A theoretical model of understanding behaviour relating to technology use)</em>.</td>
</tr>
<tr>
<td>EAI</td>
<td><strong>Early Alert Indicators</strong> <em>(a predictive learning analytics dashboard which helps to identify students’ progress)</em>.</td>
</tr>
<tr>
<td>EE</td>
<td><strong>Effort Expectancy</strong> <em>(The extent to which a user of technology perceives a system as easy to use and its impact on behavioural intention)</em>.</td>
</tr>
<tr>
<td>ET</td>
<td><strong>Eye-tracking</strong> <em>(Determines where a user is gazing at any time and records eye Movements)</em>.</td>
</tr>
<tr>
<td>FC</td>
<td><strong>Facilitating Conditions</strong> <em>(Perceptions of whether organisational conditions are adequate for effective use of a technological system)</em>.</td>
</tr>
<tr>
<td>HEI</td>
<td><strong>Higher Education Institution</strong>.</td>
</tr>
<tr>
<td>HREC</td>
<td><strong>Human Research Ethics Committee</strong>.</td>
</tr>
<tr>
<td>KMi</td>
<td><strong>Knowledge Media Institute</strong> <em>(Department within the Open University responsible for the EAI dashboard development and maintenance)</em>.</td>
</tr>
<tr>
<td>OU</td>
<td><strong>Open University</strong> <em>(Distance learning university in the UK)</em>.</td>
</tr>
<tr>
<td>OUA</td>
<td><strong>OUAnalyse</strong> <em>(The short-term prediction data on the EAI dashboard)</em>.</td>
</tr>
<tr>
<td>PE</td>
<td><strong>Performance Expectancy</strong> <em>(The degree to which an individual perceives that using a technological system will help them in their job performance)</em>.</td>
</tr>
<tr>
<td>PEOU</td>
<td><strong>Perceived Ease of Use</strong> <em>(A user’s perception of how easy a technological system is to use)</em>.</td>
</tr>
<tr>
<td>PLA</td>
<td><strong>Predictive Learning Analytics</strong> <em>(Predictions of students’ learning performance using educational data analysis)</em>.</td>
</tr>
<tr>
<td>PU</td>
<td><strong>Perceived Usefulness</strong> <em>(A user’s perception of how useful a technological system is)</em>.</td>
</tr>
<tr>
<td>RTAP</td>
<td><strong>Retrospective Think Aloud Protocols</strong> <em>(A method where thoughts are verbalised after performing a task)</em>.</td>
</tr>
<tr>
<td>SI</td>
<td><strong>Social Influence</strong> <em>(The degree to which a user perceives that other people think that they should use a technological system)</em>.</td>
</tr>
<tr>
<td>SPM</td>
<td><strong>Student Probability Model</strong> <em>(The long-term predictions of whether a student will reach specific milestones during their studies)</em>.</td>
</tr>
</tbody>
</table>
Thematic Analysis (A method for identifying, analysing, organising, describing and reporting themes found within a data set)

Technology Acceptance Model (A theory explaining how users come to accept and use a technology)

Theory of Planned Behaviour (A theoretical approach which helps to understand behaviour in different settings)

Unified Theory of Acceptance and Use of Technology Model (The theory that the actual use of technology is determined by behavioural intention and is determined by four key constructs)

Virtual Learning Environment (Online learning platform, that allows teachers to communicate with and share educational materials with their students)
Chapter 1 Introduction

1.1 Predictive Learning Analytics: Introduction

Educational predictive learning analytics (PLA) refer to predictions of students’ learning performance through educational data analysis (Lu et al., 2018). The collected data are aimed at providing students with support and improving retention. Learning Analytics is defined as ‘the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs’ (Long and Siemens, 2011, p33). PLA have the potential to identify students at risk of failing by identifying their learning behaviour patterns and predict their grades before they fail (Gašević et al., 2016).

Higher Education Institutions (HEIs) are experiencing constant change both in terms of the student experience and lecturer expectations. Whilst the primary focus is the sharing and development of knowledge, there is an increasing requirement that lecturers adopt new and innovative ways of supporting their students including the use of PLA tools which will identify students at risk and subsequently allow for timely support (MacFadyen and Dawson, 2010). As discussed later in Chapter Two, more evidence is needed to understand teachers’ acceptance of using PLA (Herodotou et al., 2019c).

Section 1.2 looks at the fictional case study of an Associate Lecturer (AL) at the Open University (OU). It gives insight into how PLA can be used by ALs at the OU using the Early Alert Indicators (EAI) dashboard. EAI is a predictive learning analytics dashboard which helps to identify students’ progress and is particularly aimed at supporting those students who might be at risk of non-completion of their next tutor marked assignment (TMA) or failing their studies. For some ALs, EAI is seen as a useful tool but for others there are concerns based on factors such as how far algorithms can tell us what we need to know about students’ progress and how ethical it is to use PLA to inform teaching practice.

From my personal experience as an AL at the OU, one of the barriers to acceptance of EAI appeared to be influenced by the organisational structure and how far ALs were supported in their decision of whether to use EAI. Section 1.3 addresses organisational influences and outlines some of the potential barriers as to why there might be ‘resistance’ to using PLA. Section 1.4 outlines the research aims of this study before Section 1.5 explains the rationale for the methodology of this thesis which is discussed in Chapter Three. Section 1.6 concludes the chapter before moving forward to the literature review in Chapter Two.
1.2 EAI Dashboard: What Do ALs See?

On Thursday morning Daisy, an AL at the OU, was marking assignments when she remembered that the EAI dashboard would have had its weekly update on Wednesday afternoon. Keen for a distraction from marking her psychology assignments, she went to her student group page and clicked on the link to take her to the EAI dashboard. To remind herself of the process, she first clicked onto the training video here to remind herself of the dashboard functions. What Daisy saw next, was that of the 20 students on her psychology Year one module, 17 had submitted their next TMA but three had not. This was a concern to Daisy, particularly as of the three students who had not submitted, only one had asked for an extension. Student A had already contacted Daisy to explain that she had been unwell and had a catch-up plan in place. Daisy was no longer concerned about this student but made a mental note to check in with her the following week. More concerning, the other two students had not been in touch.

Student B had previously submitted two assignments on time and the EAI dashboard showed that he had been active on the virtual learning environment (VLE) up until two weeks ago, so the fact he had not submitted this one was uncharacteristic. Daisy clicked onto his individual profile and could see that his prediction showed that there was a 75% likelihood he would not submit his next TMA. Concerned by this, Daisy had a few options available to her, she could contact Student B and check if there were any reasons as to why he had suddenly changed his study pattern. She could also contact the student support team (SST) to ask if he had been in touch with them and if necessary, arrange for an additional support session to help him catch up. Moving her attention to Student C, she could see that despite not having submitted her TMA, she was still active on the VLE and was accessing the module materials as frequently as the average student. Daisy was concerned as to why she had not submitted her TMA but a quick email out to remind her that the deadline had passed and that she could give her an extension would suffice for now. Daisy also remembered that having done this in the past had resulted in a student staying on the module because she had used the opportunity to support the student before they got so far behind that they withdrew from their studies.

Daisy is a passionate AL who understands the problems some students at the OU face when managing part time education, families, and work. To counter this, she uses all tools at her disposal to offer the support needed to ensure that the learning journey of her students is enjoyable and successful. One of the tools she uses is EAI, but she equally understands that there is scepticism among her AL colleagues about using PLA as a teaching tool. On discussion with Pilar her colleague (who is equally passionate as Daisy about her students) Pilar stated that she is concerned about how algorithms can tell us what we need to know about students and wondered if the predictions were always accurate. She is less confident in using data particularly when it includes interpreting
graphs and diagrams. Pilar prefers to stick to her existing teaching approaches of learning the study patterns of her students and ensuring regular communication. She told Daisy that her intuition about a student is usually correct, so she is happy to use this rather than relying on algorithms. Another concern voiced by Pilar is that she has reservations about how far students consent to their data being used for PLA and whether their consent is explicit or implicit.

Pilar is not alone in her concerns about using PLA and nor are her concerns specific to the OU. A study by Kaliisa, Mørch and Kluge (2021) found that there was teacher scepticism regarding the evaluative role of PLA, and whether it captures the most reliable predictors of student learning. Their findings indicated that teachers’ personal experiences were a major influence on their adoption of PLA. They also found that whilst teachers recognised the value of PLA, there was scepticism as to whether it accurately represented students’ learning behaviour much of which cannot always be predicted either by the student themselves or their tutors.

One of the differences between Pilar and Daisy is the belief system they hold about using predictive data to support students. Dewey (1933, p. 6) described belief as ‘something beyond itself by which its value is tested; it makes an assertion about some matter of fact or some principle or law’. Teachers’ beliefs are the more specific assumptions about teaching and learning held by teachers such as their efficacy (confidence in providing appropriate support to students), epistemological beliefs (the nature of their understanding of knowledge) and self-efficacy (their confidence as educators) (Pajares, 1992). Existing knowledge, skills and experiences are not necessarily accurate predictors of actions because the beliefs system the person holds will be a powerful influence on their choice of action (Bandura, 1986). Beliefs about one’s personal competence therefore influence the choices made and the courses of action they pursue. For example, the higher one’s self-efficacy, the more likely they are to carry out an action (Bandura, 1997).

For Daisy, the use of PLA is part of a strategy she chooses to use, whereas for Pilar it is not. Neither is right or wrong and both can successfully support their students.

Understanding the beliefs and attitudes as to how teachers make strategy decisions can go some way towards helping to understand why some teachers embrace the use of PLA where others do not. Research into the use of technology as a teaching tool (discussed in Chapter Two) has shown that in line with the concept of self-efficacy, teachers who held positive attitudes towards both data interpretation and use of technology in general, are more likely to look favourably on its use than teachers who do not share this belief (Chao 2019). Findings from a study by Sadaf and Johnson (2017) showed that teachers’ integration of digital literacy were related to their behavioural beliefs about its value in
improving student outcomes (Chapter Two, Section 2.5.1.2). Having some insight into why an AL (such as Daisy) might use the EAI dashboard and others might not (such as Pilar) may help in drawing inferences not only about its usefulness, but also about how decisions to adopt (or not) the use of PLA are made.

The following section introduces the EAI dashboard used at the OU by ALs and explains what they see when they log on to the dashboard.

1.2.1 Early Alert Indicators Dashboard at the OU: Overview

The EAI analytics dashboard is one of the most used PLA dashboards for higher education in the UK for identifying the student progress on their learning module (Herodotou et al., 2020b). It comprises of two elements. Firstly, the Student Probability Model (SPM) which produces the long-term predictions of whether an individual student will reach specific milestones during their studies. Predictions or probabilities in the SPM model are based on indicators generated through logistic regression of a set of 70 explanatory variables. These predictions are generated at the start of the module and updated at the four student fee liability points (FLP): the four points at which fees can be refunded throughout the year if a student withdraws e.g., FLP 1 allows for 75% of the fees to be refunded FLP allows for 50% refund FLP 3 allows for 25% refund and at FLP 4 the full fees are payable with no refund. The SPM was initially developed by Calvert (2014) as an independent dashboard and was further developed to work in conjunction with OUAnalyse (OUA) discussed below.

Secondly, OUA uses short term predictions of student outcomes using machine learning algorithms and provides information on each student in an AL’s tutor group. OUA originated as a tool developed by the OU Knowledge Media Institute (KMi) as a machine learning system to identify the short-term probabilities of a student submitting their next tutor marked assignment (TMA). OUA predicts when students are at risk of non-submission of their next TMA and provides manageable data in the form of visualisations on a weekly basis. It uses a traffic light system to pinpoint in red, students at risk of either a fail grade or non-submission. Amber indicates those students with a moderate probability of failing or achieving a low pass grade. Green indicates those students who are likely to submit and gain a pass grade of 55% or above. Two types of data are utilised for calculating predictions: firstly, static data demographics, such as age, gender, previous education, geographic location, and secondly, fluid data, such as student activity on the VLE. Figure 1 shows the overall VLE activity for the whole cohort of students on the module. Figure 2 shows the information for ALs regarding their tutor group.
Figure 1. VLE Engagement of the present year cohort (all students) measured against the activity of the previous year

**VLE engagement graph for the overall cohort**: an interactive graph indicating the overall cohort engagement (brown) measured against the average of the previous year cohort (blue). Columns indicate TMA scores (brown) measured against the average of the previous year. The trend lines indicate weekly VLE activity, measured as the number of mouse clicks as an average compared with the previous year. From this example we can see that overall activity is similar across both years.

Figure 1. VLE Activity for the present year cohort measured against the previous year.
Figure 2 refers to information for ALs regarding their tutor group and is more specific to their own students rather than the overall cohort.

**Figure 2. Information for ALs regarding their tutor group**

**Student Information.** The list of students and their TMA marks. **Next TMA predictions.** The likelihood of the student submitting their next TMA (green = submit, red = non submit). Blue bar indicates the percentage risk of non-submission (the longer the bar the higher the risk of non-submission) Grade prediction indicates the predicted grade for the next submitted TMA. **Long-term predictions.** The likelihood of completion and passing the course according to the last recorded long-term prediction update

Figure 2. Anonymised OU student data of a tutor group indicating the predictions as to whether students will submit their next TMA.

Figure 3 is the data specific to an individual student and their activity on the VLE compared to the average for students on the same module in the same academic year.
Figure 3. Individual student activity on the VLE

**VLE engagement graph:** An interactive graph indicating the individual student’s engagement (brown) measured against the average student in the cohort (blue). Columns indicate prior TMA scores (brown) for the student measured against the average for the cohort. Trend lines indicate weekly VLE activity, measured as the number of mouse clicks made during each week of the course (brown) and measured against the average of students studying the same module in the same year. This student shows a different pattern to the average but with ongoing activity.

(Ctrl click for Ch 5 Section 5.2.3)

Figure 3. Data specific to an individual student and their activity on the VLE (brown) compared to the average for students on the same module in the same academic year (blue).

Figure 4 is the individual data of students’ progress on their module of study. It shows the long-term and short-term predictions, the grade prediction and an explanation of what the prediction indicators are based on such as the activity on the VLE, previous modules studied and demographic information such as the student’s occupational status.
**Long-term predictions**: these predictions are recorded as a percentage of likelihood of the module completion by an individual student. They are generated at the start of a course and at three further points throughout the module which coincide with the fee liability points (FLP) for module payment.

**TMA predictions and scores** provides predictions of future TMA submissions (S) or non-submission (NS). The extension column indicates whether a student has requested an extension for their next TMA. Each prediction is accompanied with the list of most significant indicators that contributed towards the generated, for example previous qualifications achieved, activity on the VLE and whether they have submitted previous TMAs. **Prediction history briefly** summarises the previous predictions.

By combining the SPM long-term predictions and the OUA short-term predictions, EAI has the potential to provide an early trigger of a student’s difficulties therefore providing ALs with an opportunity to intervene at an earlier stage to offer support or advice. As briefly outlined in the case study of Daisy (Section 1.2) contact/intervention could lead to: (a) the student receiving additional support and submitting their TMA, (b) the student receiving an extension and submitting their TMA later, (c) the AL initiating a managed withdrawal or deferral of the student with or without assessment banking (deferral to a later presentation of the module at the same point). Whilst identifying students at risk, it also has the propensity to help ALs to assess whether their students are on track to successfully complete their learning tasks.

My interest in discovering more about the relatively low adoption of using EAI at the OU (Figure 5) stemmed from these anecdotal observations of ALs such as Daisy and Pilar and from my time as an AL providing training and briefing sessions to other ALs on how to use the EAI dashboard. One observation was that very few ALs took the opportunity to
attend the voluntary training sessions. Those who did mostly stated that they found the training useful, yet interest in its continued use was patchy, with some ALs adopting it in their practice, while others used it only occasionally or stopped using it altogether. Again anecdotally, reports from AL colleagues into why they no longer used it systematically varied with suggestions that it took up too much of their time, they didn’t understand how to work with the outcomes, or they were overwhelmed with existing systems changes at the OU (discussed in Section 1.3). Other concerns included how far students were aware that ALs were using this data to monitor their progress (Chapter Two, Section 2.4.1).

On further investigation and to explore whether my anecdotal observations were accurate, statistical data was provided to me by KMi at the OU and regularly updated up until 2021 (Hlosta, 2021). The uptake of the use of the EAI dashboard was at 23%; 998 of the 4340 ALs teaching on undergraduate modules using EAI in 2020/2021 (Figure 5). What we can see from the graph is that over the years there have been increasing numbers of ALs given access to the EAI dashboard, but the uptake peaked in 2018-2019 when 37% of ALs were using it during the final part of the pilot roll out stage of the EAI project. At the point of the roll out to all ALs teaching undergraduate modules in 2019-2020, it dropped to 27%. In 2020-2021 this dropped further to 23%. This can be interpreted that a significant number of ALs (who chose to do this voluntarily) were using EAI. Conversely this could be considered as the majority of ALs do not use EAI despite the likelihood that it can improve outcomes for students and improve the overall retention. It is important to note that the data has limitations as it does not explain whether this is systematic use (e.g., weekly, or fortnightly) or whether it is a one-off action (e.g., someone has accessed it once but not returned).
On further investigation into the potential reasons why there might be some resistance to using PLA, it became apparent that the low adoption of using PLA was not confined to the OU. Muljana and Luo (2019) explored the perception of teachers regarding their intent to use PLA. Their findings indicated that teachers agreed that PLA had potential for supporting students through their studies however, adoption was limited. West et al., (2016) identified from their research of 276 HE campus-based teachers in Australia and New Zealand that roughly 85% of participants reported interest in attending PLA training, but very few attended and only 37% of teachers who participated reported PLA as useful to support teachers in supporting students. Of these, very few used PLA regularly (e.g., weekly, or fortnightly). This appeared to be in line with findings from Kaliisa et al. (2021), and Herodotou et al. (2019c).

### 1.3 Organisational Influences

In looking into the possible influences as to why there was low uptake of EAI use, one line of enquiry was the organisational structure and the influence of ongoing changes to the role of ALs. Like many universities, the OU has been undergoing structural changes and particularly with a new core systems IT process which has in turn affected the systems ALs have had to adopt. Some ALs are uncertain about the ramifications of a forthcoming contract change to a more permanent employment base, as presently ALs work from part-time contracts with additional day lecturer contracts for role-related duties. From August 2022, this will change to become a permanent contract based on full-time equivalent hours (FTE). As many ALs hold posts outside of the OU they are uncertain how this will affect their working practice. Other changes include the introduction of a new marking tool which is being implemented and will change the way in which marking is carried out and recorded. In research at the OU looking specifically at the AL role in the use of EAI.
Herodotou et al. (2019c) found that teacher-related changes at the OU (such as changes to tuition policies, employment contacts) meant that some faculties were reluctant to roll out EAI initially, which also created a potential barrier to ALs accessing the dashboard. From this, it seemed likely that the potential barriers to its use were not always teacher-focused, but that they were also due to organisational decision-making. ALs are invested in working to ensure that new initiatives are functional and workable, and as the use of EAI is not mandatory, for some faculties the priority was to adopt those new systems rather than EAI. From my perspective as a researcher trying to understand resistance, the reasons for relative low adoption of EAI were more complex than individual choice and beliefs and there were several processes which needed to be considered as to why EAI was not adopted by more ALs.

Where there is resistance to adopting any new initiative or where there is dissent, there is often the assumption that it stems from an individual’s resistance to accept change, when the reasons to challenge change can be more complicated. Early approaches to managing resistance to change have tended to focus on ways to encourage acceptance rather than examine what the change might mean for both individuals and groups of employees. Kotter and Schlesinger (1979) for example, identified the four main reasons for resisting change as 1) parochial self-interest and perceived threat (concerns for their own position rather than for the organisation). 2) Low tolerance for change generally (resisting the upset change can have on stability). 3) Misunderstanding of what the change might mean for them as an employee which might be driven by 4) poor communication about the changes ahead. On examination of their theory the focus appears to blame the change recipients’ behaviour when change is not adopted. This fails to recognise that resisting change might be a powerful and effective tool particularly if considering a highly skilled workforce who may see problems that the organisation does not acknowledge (Ford, Ford and D’Amelio, 2008). As noted by Dent and Goldberg (1999) the predominant perspective on resistance has tended to be from the organisation.

Piderit (2000) has also critiqued research on resistance to change for its failure to understand that those who resist organisational change often do so with good intentions thus, there is a tendency to assume resistance is a negative phenomenon when it is actually more complex. She indicated that that there were often positive reasons for negativity towards organisational change, such as an ethical position, for example, to prevent what could be damaging change to an organisation that an employee has invested their time and effort in. She cited three dimensions to responses to change. 1) Emotional; the individuals’ feelings about the change which could be evoked as frustration. In relation to this, some of the initial resistance to using EAI was potentially organisational insofar as ALs are paid on a contract basis and additional duties are paid for. As there was no mandate to use EAI, there was anecdotal evidence (from my
experience of carrying out training sessions) of resistance to its use, based on it being an additional unpaid task. This was also evidenced by Herodotou et al. (2019b) in interviews as part of a wider OU study into the use of PLA, where lack of payment for the training to use EAI was cited as a reason some ALs did not use it. 2) Cognitive; the individual’s belief about the change (be it positive, negative, or neutral). This links specifically to the beliefs teachers hold about using PLA and whether it fits with their belief system (as discussed in Section 1.1). Addressing this from the perspective of ALs using EAI, with the correct processes for support in place and with the intrinsic beliefs of its usefulness, beliefs can be a powerful tool in the acceptance of its use if strengthened by organisational support. From my own perspective as an AL who conducted briefing sessions to colleagues on how to use the EAI dashboard, EAI was viewed positively by ALs to support student success, but emotionally shifting from their existing belief system to accept a more data-driven approach was challenging for some, and because it had not formed part of their teacher training it was sometimes seen as a bit of an unknown quantity. From this, there was evidence that there was no one single reason for low adoption and that understanding the more nuanced behaviours of ALs in PLA use would provide insight into what influenced why some ALs adopted it and others did not. 3) Intentional: based on behaviours, for example, past experiences of the organisation and the implications of the change for the future.

Within these responses there may be positive and negative effects occurring together to create ambivalence, for example where there is conflict between their emotional and cognitive responses. This is in line with the views of Dent and Goldberg (1999) who argued for a redefinition of resistance as it is often not that people resist change but that they resist the effects of the change (such as the loss of pay or working conditions) hence they argued the term resistance to change is inaccurate and potentially misleading.

One approach to understanding resistance (and particularly given the findings from the OU) could be explained by the position tendered by Armenakis, Harris and Mossholder (1993) who defined resistance as a cognitive state and call it ‘(un)readiness.’ They made the differential between ‘readiness’ and ‘resistance.’ Readiness is the behaviours which pre-empt how change is adopted and is described in terms of the organisational members' attitudes, beliefs, and intentions towards the proposed change. They argued that the way in which change is approached is fundamental to whether it is accepted or not. Interpersonal and social dynamics need to be considered for readiness to be created. Beyond this, Armenakis, et al. (1993) argued that ‘readiness’ support should not be confined to pre-change situations but that it should be ongoing and guided by the urgency of the change to ensure support to adapt to changes as needed by those involved. From studies carried out at the OU Herodotou et al. (2016; 2017; 2019a; 2019c 2020a; 2020b; Rienties et al., 2016a) there is evidence to suggest that resistance to using EAI is at least in part, borne out of the need for preparation and organisational input to support its use.
Whilst addressing organisational change is not the intention of this research, it inevitably forms part of the line of questioning and is an area of potential research for future development.

From the observations of my practice as a user of EAI and a trainer of other ALs in how to use it, there was evidence of multiple reasons why they may, or may not use EAI. This and the previous sections have offered an insight into some of the underlying reasons why this research was necessary.

1.4 Research Aims

This research was designed to determine the reasons for some of the barriers to PLA use and addressing ways in which these barriers can be overcome. The research builds on the existing stream of work carried out at the OU into the use of PLA discussed in Chapter Two (Herodotou et al., 2016; 2017; 2019a; 2019b; 2019c; 2020a; 2020b; Hlosta et al., 2017; 2020; Kuzilek et al., 2015; Rienties et al., 2016a). It contributes to ongoing OU strategy initiatives such as The Open University Strategic Plan 2021/22 and Objectives initiative of investing in technology that enables success. It also contributes to the broader literature seeking to understand resistance to technology acceptance. This research is therefore relevant to teachers, managers, and student support services with an interest in understanding why there is reluctance to using PLA and what strategies might be employed to encourage teachers to look at ways of incorporating it into their teaching practices. The potential causes of resistance or unreadiness should therefore be appreciated taking account of individual and cultural differences particularly given the unique role of ALs at the OU.

1.4.1 Research Questions (RQs)

| 1) How do existing teacher beliefs influence Associate Lecturers’ use of PLA? |
| 2) How does knowledge of (a) technology and (b) data literacy relate to Associate Lecturers’ use of PLA? |
| 3) What are Associate Lecturers’ (a) perceptions of the use and usability of PLA and (b) actual use as measured by fine-grained eye-tracking approaches and observation of use? |

By addressing existing teacher beliefs towards using PLA, RQ1 identifies the reluctance or ‘unreadiness’ amongst some ALs to using EAI and whether this is a phenomenon specific to users of EAI. It examines how far teacher beliefs influence decisions on whether to adopt its use.

Given the nature of the OU being an online distance HEI, most ALs have at least a working knowledge of technology and data literacy but may not have the necessarily
expertise in using PLA dashboards which includes aspects of technology and data literacy they may not be expected to use in their AL roles (such as interpreting data). RQ2 identifies whether there are gaps in ALs technology use and their data literacy in general which influence whether they use PLA.

Finally, I examine whether the functions and design of the EAI dashboard create barriers to its use based on the perceptions of its usability (RQ3). RQ3 takes both a quantitative and qualitative approach by using eye-tracking technology to observe and plot ALs’ use of the EAI dashboard followed by Retrospective Think Aloud Protocols (RTAP) interviews to give a clearer picture of what some of the practical barriers might be, and whether gaps in understanding can be explained through the quantifiable observation of use. It also uses a qualitative approach using a screen-sharing observation and Concurrent Think Aloud Protocols (CTAP) interviews to observe EAI use. Observation using eye-tracking is a new line of enquiry in understanding the use of EAI and PLA in general; and can be used to inform dashboard developers and which design areas are specifically useful and they should improve. Moreover, I argue that self-reports of PLA use are only a part of the picture as they only identify what is already known (what ALs are aware of) where fine-grained observation gives additional information ALs may not be aware of when self-reporting such as functions of the dashboard they do not use.

The research is sectioned into distinct studies based on the participation of 11 ALs as follows: 1) Self-reports of how ALs use EAI through semi-structured interviews with all eleven (N=11) participants. 2) Comprehensive and measurable observation of ALs’ use of EAI using eye-tracking technology and RTAP with six (n=6) of the 11 participants. 3) Observation of the actions taken by observing use through screen-sharing and CTAP with five (n=5) of the 11 participants¹ (Figure 6).

¹ Due to the Covid-19 restrictions, it was not possible to continue with eye-tracking therefore study three was added as an alternative using screen-sharing observations.
Figure 6. Research design structure of the three studies conducted

1.5 Methodology

Chapter Three addresses the methodology used for this research which takes a mixed methods approach. Semi-structured interviews were combined with observations of actual use. The use of eye-tracking, observation, Retrospective Think Aloud Protocols (RTAP) and Concurrent Think Aloud Protocols (CTAP) as a methodology (discussed in detail in Chapter Three) was chosen for this research to facilitate a deeper understanding of the use and usability of EAI.

Semi-structured interviews allowed for self-reports of participants’ beliefs and experiences of using EAI (RQ1) and confidence in technology use and understanding data (RQ2). Eye-tracking was chosen as a method to gain a deeper understanding of EAI use; existing educational studies have shown it to be a useful way of understanding not only the beliefs of teachers from their own perspective but also how EAI is used and whether it is used effectively (RQ3). Eye-tracking has not been adopted as a method for specifically understanding teachers’ engagement with PLA, it has however been adopted widely in educational studies with students. For example, Hu and Gu (2017) used eye-tracking to identify how students solve complex analytical problems. By measuring eye fixations within certain areas of interest (AOIs) from this they were able to identify that high-performers spent longer looking at analytical problems than students who were not identified as high performers.

Findings from this study were particularly relevant as the EAI dashboard contains several forms of graph visualisations (Section 1.2.1 Figures 1-3). Goldberg and Helfman (2010) pointed to the fact that data analysis can be complex and time-consuming due to the
amount of data generated. From the perspective of the EAI dashboard there are multiple actions to interpret therefore by using eye-tracking and screen observations alongside RTAP and CTAP is a way of observing both actions and accuracies in terms of use and usability. This combined with the interviews of AL experiences allows for more depth of understanding not only why ALs do or do not engage with EAI but also how they use it.

1.6 Conclusion

Chapter One has situated this study within the academic context of existing PLA studies and how EAI is available to ALs as part of their teaching tools. It has briefly outlined the issues which led to this study to better understand the reluctance of ALs to use EAI systematically.

Chapter Two is a narrative literature review which addresses the wider existing studies explaining teachers’ experiences of using PLA, and critically evaluating its role as a teaching tool in HEI. It also evaluates existing studies carried out at the OU and situates my position within that stream of work. The ethical use of student data in PLA emerged as an area of concern for participants (Chapter Three Section 3.4.1) and forms part of the literature review both in relation to the OU and wider studies. Theoretical models and seminal works that underpin the understanding of behaviour, attitudes, beliefs, and intentions in technology acceptance have been reviewed: The Theory of Planned Behaviour (Ajzen, 1991), The Decomposed Theory of Planned Behaviour (Taylor and Todd, 1995), The Unified Theory of Acceptance and Use of Technology (Venkatesh, Morris, Davis and Davis, 2003). These theories were identified as those which would provide the most effective basis for evaluating existing educational studies which focus on the use of technology as well as PLA and could therefore inform this research for addressing RQ1 and RQ2. From here gaps in knowledge have been identified and discussed which have led to a conclusion that no single theoretical model can act as an adequate framework for understanding PLA acceptance.

Chapter Three is a discussion of the methodology journey. It looks at some of the changes that have taken place both theoretically and practically. It also identifies the complex issues which arose from Covid 19 and its impact on the study.

Chapter Four is the thematic analysis of the eleven (n=11) semi-structured interviews which form study one and is informed by the theoretical models and findings from research studies discussed in Chapter Two.

Chapter Five is the analysis of six (n=6) quantitative eye-tracking and RTAP (Study Two) and five (n=5) qualitative screen-share observations and CTAP interviews (Study Three) which were carried out when Covid-19 restrictions prevented further face-to-face interviews.
Chapter Six discusses the combined findings of the three studies and implications of this research. It concludes the study research, returns to the original research questions and addresses the extent to which they have been met, and refers to my reflexive engagement with the research. It also examines the limitations of the study alongside recommendations for future research.
Chapter 2 Literature Review

2.1 Introduction

Chapter One has outlined the rationale for this thesis and discussed the role of Early Alert Indicators (EAI) at the Open University (OU). It has suggested some of the possible reasons explaining why EAI is not adopted by some ALs. It has also identified that there are both intrinsic (based on teacher beliefs) and extrinsic (organisational influences) reasons why EAI might not be adopted by some Associate Lecturers (ALs), and it has provided a rational for the methodology discussed in Chapter Three. Moving forward, this chapter examines the literature that has informed the existing body of work in the field of Predictive Learning Analytics (PLA). It begins with an outline of the methods used to review literature in Section 2.2.

Section 2.3 addresses the present stream of literature pertaining to teachers’ use of PLA both in the OU and in other educational settings. It concludes with a critical evaluation of the research to date. Section 2.4 then addresses the existing ethical considerations of using predictive data and evaluates the potential tensions and issues arising from using student data based on existing studies to date. Section 2.5 introduces the theoretical models which were identified from the literature search as frameworks that could help to explain teacher beliefs, and knowledge of technology: The Theory of Planned Behaviour (TPB) (Ajzen, 1991), The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis and Davis, 2003), The Decomposed Theory of Planned Behaviour (DTPB) (Taylor and Todd, 1995).

Section 2.6 compares the effectiveness of each model and summarises how each one might inform a more specific framework specific to the use of PLA. It identifies the gap insofar as none of the models are specifically applied to PLA and none of them address the ethical issues of using technology. Section 2.7, I conclude that whilst each model has its strength in using constructs to help understand behaviour and technology use, no one model on its own is effective at looking specifically at teachers' use of PLA when examining the themes emerging from existing literature and the data analysis of this thesis.

The following section outlines the search methods used to review the literature relevant to this research.

2.2 Literature Review: Methods

The literature review process started in May 2018 prior to most of the data collection and analysis and it was an ongoing process throughout the development of this thesis up to 2022. I used the OU online library to access relevant literature using searches in various databases following the PRISMA statement (Moher et al., 2009) and the following
databases were selected: EDUCAUSE; SpringerLink Journals; ACM Digital Library; Sage Research Methods Online. I also searched SAGE publications. I was able to search a wide range of learning analytics journals such as the Journal of Learning Analytics and I received alerts from my membership of The Society of Learning Analytics Research (SoLAR) regarding new articles published. I also used snowballing techniques in which I used the citation history of relevant articles which I took to the OU library and searched directly for the articles. I used two library databases, initially Mendeley, and I added Zotero due to inconsistencies with Mendeley. I received email alerts by Mendeley and Zotero based on previous searches and existing articles in my library database, and I was also able to add recommended articles directly to both databases.

One strategy when I first started my literature review was to search seminal articles particularly in relation to the theoretical models. From here I used the OU library databases to find related articles using phrase searching terms such as ‘Learning Analytics’ and ‘Predictive Learning Analytics.’ I also used Boolean searches to increase the search using and Teachers and Higher Education and Visualisations, such as ‘Technology use and Teachers’, as well as searching for broader aspects of higher education teaching. Due to the content of the research no country was off limits, so studies were included from around the world and only peer reviewed articles were included. The Journal of Learning Analytics was a constant source of international studies and up-to-date articles. For work related to existing OU studies I used the OU library and the OU Research Online (ORO) resources.

Information relating to eye-tracking and Retrospective Think Aloud Protocols (RTAP) started in 2019 as part of the amendment to this study following the feedback from my initial study and the potential to work more conclusively on a methodological gap in research so far. Using screen-sharing and Concurrent Think Aloud Protocols (CTAP) was also added in 2020 when face-to-face interviews were no longer possible due to Covid-19. From the initial study evidence emerged that some ALs had concerns about the ethical use of student data therefore this formed part of my research and literature review from 2018 to 2022. Studies relating to the use of predictive analytics have also been consistent from 2018 to 2022. The iterative process is shown below (Figure 7).
2.3 Predictive Learning Analytics: What Do We Know So Far?

Research over the past 20 years has shown that the advancements in dashboards in general and PLA dashboards can provide teachers with opportunities by offering information, insight, and knowledge about their learners and their individual needs (Rienties et al., 2016b; Tempelaar, Rienties and Giesbers, 2015). With the increasing availability of learner data such static, dynamic, and demographic details, combined with PLA visualisation dashboards, there is scope for teachers to provide additional effective support to diverse groups of learners (Charleer et al., 2016; Daley, Hillaire and Sutherland, 2016; Hlosta, et al., 2015; Jivet et al., 2018). Despite the growth in interest in using PLA there is evidence to suggest that there are gaps in our knowledge as identified by existing studies and in particular systematic literature reviews of the position of research into the use of PLA dashboards to date. At present the OU only has a teacher-facing dashboard and the literature in relation to this is discussed in Section 2.3.1 below.

2.3.1 Teacher-Facing PLA Dashboards

If taken advantage of, teachers can act accordingly through early intervention and adapting teaching practices to account for student differentiation (Ifenthaler et al., 2016). Many of PLA dashboards for teachers have focused on how teachers can use the data to support students and improve overall university retention (Herodotou et al., 2020a). This section addresses some of the major studies of teacher use of PLA.
Looking specifically at study by online distance learning, it is particularly important that teachers receive feedback about their students’ progress due to the higher likelihood of students disengaging from their studies (Dourado et al., 2021). Students are less ‘visible’ and sometimes hard to contact, making teacher-student communication more tenuous in some situations, particularly when a student has multiple conflicting responsibilities such as family and work (Chapter Three, Section 3.3.2). Moreover, with the increase in blended learning and the use of online lectures to replace face-to-face sessions in student-facing universities (in part due to Covid-19) the need to find new ways of supporting students has become more relevant than ever, particularly where educators who are less familiar with teaching online have had to adapt to finding ways to evaluate their teaching practices online (Corbu and Edelhauser, 2021).

Studies into the use of PLA dashboards have shown that they have the potential to be used as an additional tool for teachers to gain a better overview of students’ progress (Munzner, 2014; Herodotou et al., 2019c; 2020a). They also provide an opportunity for teachers to reflect on their teaching practice and develop their skills (Klerkx, Verbert and Duval, 2017). More relevant to this study, it allows for timely interventions by teachers to identify and ‘save’ at-risk students (Herodotou et al., 2017; 2019b; 2019c; 2020a).

An early example of a teacher-facing PLA dashboard was Purdue University’s Course Signals. Purdue was one of the first universities to use PLA to enable teachers to provide real-time feedback directly to students by using demographic characteristics, past academic history, and students’ effort as measured by interaction with Blackboard (their online learning platform). Students at Purdue were in direct receipt of the data and received personalised emails which were shared with their teachers. The findings of studies into the use of PLA at Purdue showed improvement in performance and the retention of first- and second-year students (Arnold and Pistilli, 2012). Students expressed positive experiences with Course Signals overall, with 89% of respondents reporting that they found the information teachers shared with them helped to improve their study outcomes. Teachers at Purdue voiced however, concerns regarding increased workload in using the dashboard. They noted the risk of students not developing independent learning skills when teachers have control over the responsibility for prompting them to engage in study.

Findings from a study by van Leeuwen (2015) identified that while PLA dashboards can help improve student outcomes, they have a further impact in that they are also beneficial tools for teachers in increasing their confidence. Using computer supported collaborative learning, two studies were conducted comparing outcomes for two groups of teachers one of which used PLA while one relied on traditional teaching strategies alone. Findings showed that in the first study which focused on social activities, the teachers who had the benefit of PLA were more able to identify student problems than those who did not use
PLA. Conversely, this was not the case for the second study which focused on cognitive activities and PLA did not appear to have any influence on outcomes; those teachers who used PLA were able to identify and target support to students who were experiencing difficulties. van Leeuwen (2015) concluded that PLA had a positive effect on teachers’ ability to target student support and carefully balance their approach to maximise student potential by providing real-time evidence. Also, teacher confidence was increased by having the additional understanding of student needs.

Other areas of research have focused on raising questions as to whether PLA dashboards fulfil their intended purpose such as having a positive impact on learning. Ferguson et al. (2016, p. 28) pointed out that empowerment in education comes in different forms and should address the ‘human side of learning’ therefore PLA needs to develop to take account of new pedagogies which in turn will encourage the confidence in PLA use. This concern is shared by Schwendimann et al. (2016) who carried out a systematic review of 55 studies of PLA dashboards based on four categories: 1) types of contribution (e.g., theoretical proposal or framework), 2) learning context (e.g., target users and learning scenarios), 3) learning dashboard solution (e.g., purpose and data sources), 4) evaluation. Findings showed that the 58% of studies proposing their use did not evaluate their effectiveness for either students or teachers. Limitations to effectiveness therefore again point to the degree to which the intended users are involved in co-designing them and their data literacy is considered, as determinants of how they are used (Echeverria et al., 2018; Howell et al., 2018).

Teachers have also noted insufficient support (e.g., training) and communication as a challenge to implementing PLA (Tsai and Gašević, 2017). This suggests that left to their own volition, teachers are unlikely to use PLA but with the correct support resources and conditions they might be more inclined (Ifenthaler and Yau, 2019; Kaliisa, Kluge and Mørch, 2020; Muljana and Luo, 2019). The review addressed the indicators used in each dashboard and identified that research into the use of teacher-facing dashboards or PLA dashboards is still in its infancy. In part this is because to date most dashboards have only been developed as part of an exploration into their efficacy and to test their feasibility. To this end, reports into empirical findings of dashboards’ effectiveness vis a vis student outcomes were limited.

Also in recent studies, Kaliisa et al. (2021) carried out a qualitative study using semi-structured interviews with 16 (N=16) teachers at two Norwegian universities (The University of Oslo and Oslo Metropolitan University) to understand teachers’ perspectives towards PLA dashboards as a potential tool to support course design practices. Participants were from a mix of blended and face-to-face teaching situations and were asked about their role, their course design practices and their perspectives on
PLA as a teaching support tool. Participants highlighted several challenges to PLA which concur with the findings from studies at the OU. First, all 16 teachers agreed that PLA added to their existing busy workload, others reported that they already worked under pressure and that because it would lead to follow-up work it was unrealistic within their working situation. Thus, their motivation and incentive to use a PLA dashboard was low. These findings are concurrent with OU study findings where some ALs disagreed with the idea of using PLA to follow up with students at university level where students are expected to learn independently (Herodotou et al., 2017). A criticism of this approach is that for some students (and particularly OU students) who often have a specific demographic such as choosing online study to combat the stress of attending a traditional university, physical or learning health needs, or low confidence in attaining the required entry requirements for traditional universities, the move to become an independent student learner is more complex. Thus, it is not always appropriate to assume that all students enter their studies with the same needs.

One of the most prevalent findings from reviewing the existing literature reviews identifies that there is still only limited research into the use of PLA dashboards, especially at large-scale, and it is yet to be fully developed. The following section details existing literature related to PLA at the OU, which forms the foundation for this research.

### 2.3.2 Studies from The Open University, UK

This section looks specifically at studies looking at teacher-facing PLA which have been conducted at the OU (Herodotou et al. 2017; 2019a; 2019b 2019c 2020a Rienties et al. 2016a) The OU has consistently evidenced the potential of PLA to support students who are at risk of failing and teachers in better monitoring their students, yet there is still room for PLA to be used more effectively by teachers.

Early studies from the OU looked specifically at data from the virtual learning environment (VLE) to predict students at risk of not submitting their next assignment with the intention of understanding student behaviour by looking at their data alone and to therefore predict their risk of not completing their module. The VLE ‘clicks’ are indicators of how often a student accesses their module online. Wolff et al. (2013) analysed three level one (first year) courses (modules), firstly by looking at all VLE clicks, and then by breaking it down by the VLE data categories. Findings indicated that VLE activity increased shortly before an assignment was due. They also found that students could access the VLE at this late stage and still pass the assessment. Some students who clicked a lot still failed or did not submit, whereas others hardly clicked and still passed. Some explanations for this are the possibility that students have downloaded the module materials or may have been retaking the module therefore they are not as reliant on the VLE. Wolff et al. (2013) concluded that the VLE clicking behaviour of students is an indicator of activity, but on its
own it cannot predict student outcomes; therefore, the use of both fluid and static data is more accurate for making predictions. Whilst the VLE clicking behaviour of students gives teachers an indication of engagement it is only a part of the bigger picture. As with other PLA dashboards, the EAI dashboard has developed over time to include more sensitive and accurate outcomes.

Whilst the study carried out by Wolff et al. (2013) identified one specific indicator of student behaviour, in further research Herodotou et al. (2017) carried out a large-scale study with the 240 teachers in 10 modules involved in the initial pilot of the OUAnalyse (OUA) dashboard to understand how teachers use PLA to support students at risk of not completing or failing a module. As outlined in Chapter One Section 1.2.1, the EAI dashboard has evolved over the years; the student probability model (SPM) was not embedded in the EAI dashboard when this study was conducted, but only OUA\(^2\) was, and therefore the latter comprised the focus of the above study. Data were collected from statistical analysis of 17,033 students’ performances, teacher usage statistics, and five individual semi-structured interviews with teachers. Findings revealed that teachers used predictive data to support their teaching practice and students yet in diverse ways.

A summary of findings from Herodotou et al.’s (2017) study showed that one participant saw it as additional work to do and not helpful, particularly at the beginning of the module as the data was not sensitive enough to make an accurate prediction. For this participant, the module taught relied on literacy and numeracy skills, and what OUA was not able to do was help her to identify students who needed help with these areas; had this been possible it may have positively influenced her decision to use it. Another participant viewed it more positively and suggested that by being able to access VLE activity data, she was able to monitor students at the times in between submitted work, whereas she would otherwise have to wait until the submission date of the next assignment. Capturing data information early meant she was able to make timely support referrals. Being able to view VLE data, also helped her to know when to devise specific activities to engage students during drought periods of contact. It did not however, tell her if they were otherwise engaged (e.g., on forums) and keeping up with their study planner activities. A third participant found access to VLE data useful to identify students who stopped engaging with module materials and was therefore able to intervene accordingly. The fourth participant reported that it brought together information about the students and reinforced the fact that her teaching was appropriate. She liked the fact that it gave her an early indicator of risk, rather than waiting for the submission deadline to see if students submitted. The fifth participant reported that it was not as useful because there were many

\(^2\) OUA was the original data available to ALs up until 2018 after which it was updated to EAI which incorporates both OUA and SPM
offline elements to the module taught and this was not captured by OUA. What it did do, was tell her what she considered she ought to know anyway, hence backing up her understanding.

These findings indicated some mixed results: there were clear indications that OUA was useful for the prediction of students at risk, and other studies (Rienties et al., 2016a; 2018) also indicated the successful use of PLA in various settings. But there is a mixed response to how ALs use the data with each AL interviewed devising their own way of using it. Results from the study suggested that ALs may not have been sufficiently empowered to work with the data due to time, resources available, and the organisational structure; particularly as there had been a lot of organisational change in the OU at this time with the introduction of new online systems and a new teaching platform (Chapter One, Section 1.3). Importantly, there were study limitations as the interviews were based on only a small sample of self-selected ALs from a potential field of 240 (so by definition they expressed interest in participating in the study).

In a further study, Herodotou et al. (2020a) identified the potential for PLAs to support student support staff (SST) identify and intervene with specific groups of students, at risk of failing through a motivational intervention (phoning, emailing, and texting students). For this study they looked specifically at the long-term predictions of the SPM (Chapter One, Section 1.2.1 Figure 4) which predicts the likelihood of students remaining on their module at four milestones linked to their four fee liability points (FLP) (the points at which fees are payable if still enrolled on the module). The research looked specifically at undergraduate students (N=630) with a low probability of completing their studies. Students were randomly allocated into two groups: an intervention group (n=318) and a control group (n=312). The former group were contacted by student support advisors who provided motivation through texts, phone and email contact prior to the start of a course. Findings identified that the students in the intervention group had significantly better retention than the control group, thus the intervention was successful for both individual student success, and for university retention. It also identified a strategy for ongoing student support teams to intervene in a timely manner. This indicated the potential of PLA to provide systematic support not only to university teachers, but also other stakeholders including SST and improve the outcomes for students as well as retention.

One of the studies carried out by Herodotou et al. (2019c) which informs this research, looked at a wide-scale study that collected both longitudinal data and learning data to address how teachers perceive, use and interpret PLA to influence students’ performance and how far it empowers teachers to identify and support students at risk. They used the determinants of Technology Acceptance Model (TAM) (Davis et al., 1989) and the Academic Resistance Model (ARM) (Piderit, 2000) to carry out a university-wide, mixed
methods study with 59 (N=59) teachers, from nine courses, reaching 1325 students to gain insights into the extent to which the engagement of teachers with OUA predict students’ performance (i.e., pass and completion rates). In particular, binary logistic regression analysis group-level measures, was performed to first identify whether teachers’ engagement with PLA (using the OUA dashboard) significantly influences pass and completion rates. Group-level measures were created by combining data between the student and teacher/course levels and were consistent within groups of students managed by a single teacher and within all students attending a single course. Individual level variables (such as age and gender) varied across all 1325 students. The study identified the average weekly time teachers logged onto OUA. Herodotou et al. (2019c) acknowledged that although they could log that teacher’s had accessed OUA, further detail such as time spent on the system and areas visited could not be determined. They did however identify that seven teachers (n=7) did not access the OUA dashboard at all. 

The higher-level users were among Technology and Education based subjects with Law, Maths and Social Science teachers having substantially lower engagement. From this they identified that although teachers had access to OUA they did not access the dashboard regularly.

Only six (n=6) participants from Engineering (n=3), Maths (n=2) and Technology (n=1) modules took part in an interview. Findings showed that most participants did not systematically access OUA however, they did access it at certain points. For some the start of the module was when they accessed it and others accessed it closer to assignment submission dates. What was particularly significant was that logging on behaviour appeared to decline after the first few weeks of the module start. Herodotou et al. (2019c) therefore concluded that lack of systematic access of OUA by teachers might have limited the potential effectiveness that OUA interventions could offer to students.

One of the significant aspects of this research is that very few studies have unpacked how teachers perceive and use insights from PLA in their daily practice as well as how this might be used to influence student outcomes (e.g., passing or failing a course). Recommendations from their study was that more research is needed in this area to gain more understanding of resistance or unreadiness to use and understanding teachers’ reluctance to systematically use PLA.

Although EAI is designed for ALs to access and support students rather than students accessing the data directly, lessons can also be learned by being aware of what students would want from PLA dashboards and how they respond to their data being used for this purpose. One of the issues this raises for the EAI dashboard, is that whilst ALs are involved in the design, students are not, and that understanding what students want from their tutors in terms of support might lead to a more collegiate process where ALs may
also feel more comfortable in using PLA to support students. Conversely however, the role of ALs within the OU puts them central to the process with ongoing involvement in its design and development (Herodotou et al., 2020a; 2020b). Throughout the roll out of EAI, ALs have been asked to feedback any concerns or suggestions for improvements based on their role and what most likely to help them in supporting students. The dashboard has a ‘provide feedback’ link enabling users to make suggestions and ask for technical help. However, this feature is not systematically used or promoted. Despite teacher involvement in the design, the problem of low take up is still an issue.

Overall, this literature review identifies that research into the use of PLA is still in the experimental learning stages of development (Bodily and Verbert, 2017; Jivet et al., 2018; 2020). Research to date is based on small-scale findings and there is scope for large-scale research. Conversely there is evidence that adoption of PLA can support student success when used effectively (Ifenthaler et al., 2016). Furthermore, whilst not specifically within the scope of this research, a further advantage of PLA is its focus on overall university retention (Herodotou et al., 2020a). Despite the advantages there remains scepticism among teachers regarding the usefulness of PLA (Kaliisa et al., 2021).

### 2.3.2.1 Criticisms of Teacher-Facing PLA Dashboards

Further critical discussion looked at the problems of the existing empirical studies and the implications for practice. Wilson et al. (2017) argued that there are potentially problematic aspects of PLA studies, and whilst there have been many reports of positive outcomes using PLA, there are still areas of concern both in how studies are reported and how PLA is delivered. They argued that the input into PLA dashboards is mainly driven by information technology departments and not the teachers who are most likely to use them. Another criticism they postulated was that in many situations, PLA dashboards are often generically produced which does not account for differences in how the curricula are delivered and the type of institution they are being delivered in.

The issue of differentiation in student learning needs was also identified as an area of concern, and how far PLA can account for these (Hlosta, 2020). Teachers use a range of skills to assess performance and learning outcomes therefore any analytics need to be carefully designed and appropriate for each context rather than applied generally. Other concerns included the data that are used to form the algorithms and the propensity for these to cause bias or inaccuracy or entrench existing preconceptions based on determinants such as age, gender or ethnicity (Wilson et al., 2017). This final criticism is addressed in the next section when considering the ethical use of student data.

Larrabee, Sønderlund, Hughes and Smith (2019) conducted a systematic review and quality assessment of studies on the use of learning analytics in Higher Education Institutions (HEIs), focusing on intervention studies. Their search terms identified 689
papers, from which only 11 studies evaluated the effectiveness of interventions based on learning analytics. This supported the assertion that there is limited current research. They argued that the literature indicated that the general quality of the research was only of moderate usefulness and that more research into the implementation and evaluation of scientifically driven learning analytics is needed before laying claim to the generalisability of PLA interventions. They argued that there is a tendency for educational institutions to implement learning analytics interventions with limited evidence of their effectiveness.

Substantial progress has been made in exploring and understanding how teachers are using PLA dashboards. While these studies provide some important insights into these new tools and approaches, relatively few studies have explored the use of PLA on a large scale in HEIs. (Dourado et al., 2021; Herodotou et al., 2017; 2019b; 2020a; Ifenthaler et al., 2016; 2021; Kaliisa et al., 2021; Munzner 2014; van Leeuwen, 2015). Studies into PLA adoption are still in their infancy and more work needs to be done to detail what the barriers to using PLA are and what can be done to encourage adoption.

Section 2.4 below addresses some of the literature on the ethical issues which relate to the implications of using student data and who should have stewardship of this. The ethical use of student data and how information is gathered and utilised has been an area of contention for many participating ALs particularly the question of transparency and how much students understand about how their PLA data is used. The following discussion will address some literature relating to how student data is used both within and outside of the OU and how far PLA data are operating within an ethical framework.

### 2.4 Ethical Implications of Using PLA

Often stakeholders (for example, student support teams, teachers, managers, and students) are not clear on the boundaries for the ethical use of data and there is a negativity towards the use of PLA despite the potential it holds to change the educational landscape (Drachsler and Greller, 2016). The Covid-19 pandemic has also increased the likelihood of technology in different forms playing a bigger part in teaching and learning as more educational institutions move towards a blended learning approach. From the perspective of PLA, ensuring ethical competency both in the design of dashboards, and in the use of the student information used to generate the data, is crucial. One of the common themes identified by ALs in this research has been their concerns as to whether the data is trustworthy and accurate and whether there is transparency with students around how their data is being used. These findings motivated a review of the literature around ethics and PLA, presented in next sections.

#### 2.4.1 Students and Their Data

As discussed in Chapter One Section 1.1 PLA is the use of raw and analysed student data to proactively identify interventions which aim to support students in achieving their
study goals (Long and Siemens, 2011). Whilst the collection of data is intended to improve student achievement and retention, it is not neutral in its application as there are wider considerations such as how consent to use data is obtained and how far confidentiality is maintained. Ensuring student confidentiality can be an overwhelming task particularly given the increased use of personal data, to an extent, use of personal data may be viewed as increasingly acceptable, particularly for those who are born into the digital era (Kay, Korn, and Oppenheim, 2012). For this group the personalisation of their data profile may be seen as normal, but there are still implications for how this data is used. As identified by Rets et al. (2021) in a study conducted at the OU, there are generational differences in the data acceptance of students. Younger students with lower self-efficacy voiced more trust in the data. Rets et al. (2021) The sample comprised of 21 (N=21) students who agreed to participate. Students used a dashboard based on the existing EAI dashboard used by ALs and were able to see their VLE engagement, the predictions of their next assignment and the indicators which lead to the predictions (such as previous results and their VLE activity in the weeks leading up to a submission). Evidence from the study indicated that it is older students who voiced concerns about the trustworthiness of PLA data where younger students were less concerned.

The collection of personal data is increasingly accepted as a norm for engagement in a range of online activities and subsequently there is an acceptance in HEIs that this will form part of the student enrolment process (Pardo and Siemens, 2014). Although it is necessary to collect data, it is not acceptable for HEIs to take a paternalistic approach: students rarely have choice around how data about them are collected, nor they are included in decisions about how their data is used (Prinsloo and Slade, 2016). Students should be able to feel assured that data collected is limited to improving their education and not for any other purpose (Cormack, 2016: Slade and Prinsloo, 2013).

Another concern is whether when students tick to accept data collection, is this sufficient and do they read the policy guidance explaining how their data is used? Questions then arise as to how far this is the individual student’s responsibility and if they choose not to read it, are they ultimately accepting the use of their data if they later decide they are not comfortable with it? Slade and Prinsloo (2013) argued that by consenting to the collection of data, students could be agreeing to a system that is unfamiliar to them in terms of its parameters, for example, they may not be aware exactly what data is collected and how it is used and stored, thus they agree to its collection because they must do so to continue to study.

Although the intention of collection and use of student data for PLA use is ethically and legally well-intended, it is increasingly possible that student data may also be used for purposes outside of their educational advancement (such as national statistics and to provide information to regulatory bodies) increasing the need for safeguards (Cormack,
For many students this might not be an issue, but policy guidance needs to clarify when data is being used in the wider field. When students agree to data use and sign up for a course, it does not indicate that they still agree to the data collection in three years’ time (Cormack, 2016). The OU asks students to accept data collection on a modular basis so for a period of nine months which mitigates some of Cormack’s concerns. However, if their end goal is to complete their programme of study, they are likely to continue to agree on a module-by-module basis and there are still gaps in knowledge as to how far students are aware of how their data is used (Ferguson et al., 2016).

Ifenthaler and Schumacher (2016) carried out a study at a German campus-based university to ascertain the views of 300 students regarding the privacy of their data and how willing they are to share personal and educational data for educational purposes. They identified that one of the main issues was understanding what students want from a PLA dashboard. They received 330 responses and presented students with statements based on three PLA dashboards. The first dashboard was based on the approach by Course Signals at Purdue (Section 2.3.1) where interventions are provided to students by email from their course instructor. Information to the student was displayed using three visual signals: red, orange, and green. The second displayed a dashboard showing general information about students such as their submissions, learning activities, their login to the system and their average performance comparisons against students in the same field of study in the form of graphs. For the third one, students were provided detailed insights into their learning and performance, including activity recommendations, and performance comparisons. The third example expanded the design principles of both the first and second dashboards to include prompting and was the preferred option which suggested that students favoured a broader approach. Ifenthaler and Schumacher (2016) found that students were reluctant to share personal data for PLA dashboards but were willing to share data relating to their studies. They were more likely to share data for the second dashboard than for the other two. They therefore argued that all stakeholders need to be equally involved when PLA systems are implemented at HEIs, and that research needs to address the conditions upon which students would be more willing to share their data.

2.4.2 The Role of Other Stakeholders in the Ethical Use of Data

There is also a danger that some HEIs lose sight that the role of PLA is to support student achievement (Gašević, Dawson and Siemens, 2015). With a variety of stakeholders (e.g., faculty leads, administrators, and student support staff) having access to student data, it can be complicated for HEIs to ensure that decisions based on this data are ethical (Cormack, 2016). PLA has the propensity to unveil new insights and can influence the relationship between the institution, teachers, students, and other stakeholders to improve outcomes for student success and to increase institutional retention levels. This is not
always straightforward, as there can be ethics breaches such as accidental identification of students or correlations which can be misleading and thus create inaccuracies, therefore the use of student data must be safeguarded (Slade and Prinsloo, 2013). From an ethical perspective, students should therefore have the right and responsibility to access and review their own data (Pardo and Siemens, 2014; Slade and Prinsloo, 2013).

Keeping information is important and organisations need to have certain data to inform students of results, degree outcomes etc. When we are addressing issues of PLA, information held is beyond this scope consequently, data privacy is more than the legal requirement, it is also an ethical and pedagogical responsibility as to how we better involve students in how their data is used (Hoel and Chen, 2018). In addressing the need for more stakeholder involvement in the design of PLA dashboards, Sun et al. (2019) identified ethical tensions among stakeholders with respect to PLA. They carried out a study at the campus-based University of Michigan to understand different stakeholders’ perceptions, attitudes, and expectations towards the use of PLA. They conducted 32 (N=32) semi-structured interviews with three groups of stakeholders (four developers, eight academic advisors, and 20 students) on the functionality of an early alert dashboard (the ‘Student Explorer’). The dashboard analysed student data aggregated from learning management systems and allowed academic advisors to identify students at risk. They identified findings in four main categories: (1) Context of usage: How the system was designed to function and how it currently operates differ. (2) Perceptions of stakeholders who held different views on who should be able to access PLA student data and for what purposes. (3) Data validity and particularly that the dashboard did not adequately convey potential issues and limitations of use. (4) Student consent and involvement and particularly that students were largely unaware of the use of their data for PLA thus they wanted more informed consent and involvement in how their educational data was used. Like Ifenthaler and Schumacher (2016), Sun et al. (2019) found that there was a tension between the different stakeholders and that to mitigate this they should all be involved in the design and development of PLA to address stakeholder concerns.

One of the challenges faced by stakeholders in the field of PLA is the development and adoption of an ethical policy upon which to practice. The following section addresses what we know so far about ethics and policy guidance.

2.4.3 Ethics and Policy

One of the concerns identified in this research was that some ALs are concerned about the ethical position of holding information about students when they may not be aware of this. Data use for PLA is not named specifically when students sign to accept the collection of their data, rather it is part of the wider data collection on enrolment. An online EAI ethics policy document (Policy on Ethical use of Student Data for Learning, 2014) is
available to teachers and students, which can be downloaded in various formats. In the context of this policy, informed consent refers to the process whereby the student is made aware of the purposes to which some or all their data may be used for PLA purposes, and this goes some way toward mitigating the risk of ethical breaches. The OU was the first HEI to develop a specific policy relating to the use of PLA and student data which is currently under review to ensure its rigour.

UK Joint Information Systems Committee Organisation (JISC) developed an ethical code of practice to help remove barriers to the adoption of PLA encountered by HEIs (Sclater, 2016). There are several ethical frameworks pertaining to PLA, for example the six PLA ethical principles by Slade and Prinsloo (2013): (1) PLA should do much more than contribute to a ‘data-driven university’. (2) PLA should include students as collaborators. (3) PLA data should have an agreed expiry date. (4) PLA should acknowledge that student success is complex and may not match the expectations of other stakeholders. (5) HEIs should be transparent about what PLA data will be used for. (6) The data collected must be essential in HEIs. Another example is the DELICATE checklist (Drachsler and Greller 2016) (Appendix 1) which addresses a combination of questions e.g., how and why are you using this data and is the data collected relevant and necessary trustworthy and anonymised? More generally, the General Data Protection Regulation (GDPR) sets out the rules that must be followed to protect the rights of individuals and give them control of the process and data that is being collected from them.

Tsai and Gašević (2017) reviewed PLA ethics policies adopted in eight HEIs and found that none of the policies suggested any pedagogy-based approach that developers should consider when designing and developing PLA tools. They also emphasised the importance of formalised guidelines to monitor the legitimacy of learning analytics. From their systematic literature review several challenges were identified including that there is a limited availability of policies that are tailored specifically for learning analytics to address issues of privacy and ethics. From a survey conducted with Heads of an e-Learning Forum it was found that five out of 53 HEIs had adopted a code of practice. The results of this UK report showed that the practice of learning analytics at HEIs lacked clear guidance that is designed for learning analytics-specific practice (Tsai and Gašević 2017).

More recently, Cerratto, Pargman and McGrath (2021) conducted a systematic literature review of the research on ethical issues in learning analytics literature based on 21 articles pertaining to HEIs and published in the period 2014–2019. They drew on Sclater’s (2016) code of practice and Slade and Prinsloo’s (2013) ethical framework as two diverse examples to inform their methodology. Sclater’s (2016) code of practice focused on removing the barriers to adopting PLA and provided a focus for institutions to deal with the barriers they faced in navigating legal and policy guidance (such as GDPR) in order that students are not disadvantaged if HEIs do not adopt PLA. Conversely, Slade and Prinsloo
(2013) took a more problematising approach addressing the power relationship between the HEI and students. They also identified the dynamic nature of students and the importance of their role being recognised as co-producers of policy. They addressed three specific dimensions, 1) location and interpretation of data, 2) informed consent, access to student data privacy, anonymisation and mitigating the risk of using student data without their explicit knowledge. 3) management, classification, and storage of data, including transparency in data management and data governance to ensure data protection.

Cerratto al. (2021) identified that transparency, privacy, and informed consent were the main areas addressed in the articles reviewed, whereas signposting students to additional support was the least discussed. Whilst their findings go some way towards informing the current situation on ethics policy studies, they concluded that, as PLA systems are still emerging, future studies on their use need to be developed, to provide a clearer understanding of the diversity and depth of the ethical issues faced.

Moving forward, the following section looks specifically at the ethical issues faced at the OU in considering the ethical basis for the use of EAI.

2.4.4 Ethical Issues for Early Alert Indicators

With regards to EAI, consideration needs to be on how information is collected and how students are informed of this. Several algorithms are used based on the demographic information which a student submits on admission and evidence of their previous education both before and during their OU studies, as well as dynamic data collected from their interactions with the VLE material and their ongoing performance. Sclater (2016) pointed to the fact that there are many algorithms which know information about you that you do not know yourself. Consequently, there is a responsibility to act lawfully and minimise adverse effects on students whilst ensuring that this is not to the detriment of maximising the benefits to their education. Hoel and Chen (2018) also voiced concerns that the assumptions and beliefs informing algorithmic decision-making are hidden and unlikely to be shared with students.

One example used in the EAI algorithms is the Index of Multiple Deprivation (IMD). It is a socio-economic UK government initiative addressing relative deprivation in UK neighbourhoods (Department for Governments and Local Communities, 2015). The data measures the percentage of people from each ethnic group who live in the most deprived 10% of neighbourhoods in England, Northern Ireland, Scotland, and Wales. It is based on seven indicators: income, employment, education, health, housing, environment, and crime levels and is an initiative to identify neighbourhood deprivation. It can be useful in identifying where students might live in an area considered to be deprived, but as this is a relative measure based on neighbourhood deprivation and not intended to make individual assessments, it cannot accurately identify individual risk factors (Department for
Governments and Local Communities, 2015). Therefore, this brings into question how far IMD is useful in identifying students at risk of non-submission or completion of a module and whether there are ethical and pedagogical reasons to collect this information. However, it is only one indicator among many, but it has raised ethical questions for some ALs at the OU as to how this informs them on how to support a student at risk, for example, does the collection of IMD data label students according to their predicted achievement according to this data and what are the implications of this?

In 2019, IMD data identified that people from all ethnic minority groups were more likely than White British people to live in the most deprived 10% of neighbourhoods in England. People from the Pakistani and Bangladeshi ethnic groups were over three times more likely than White British people to live in the most income-deprived 10% of neighbourhoods and people from Indian ethnic groups were least likely out of all ethnic groups to be living in the most deprived 10% of neighbourhoods (GOV UK, 2020). Given that this is a relative measure, it raises the ethical question of whether using IMD as a measure of students at risk is likely to overrepresent specific ethnic groups unfairly (Deas et al., 2003). If this information is being used, should students be informed of its inclusion and should ALs be guided as to how to interpret the meaning behind it? As the OU has a high proportion of overseas students and IMD is a UK initiative, it is not collecting the same information for all students, which could affect the accuracy of the EAI dashboard, therefore it raises the issue of trust in the data.

Building on the issue of trustworthiness, Hlosta et al. (2020) identified the reason why some predictions of student outcomes could be incorrect based on information which could not be collected by PLA data such as computer issues, problems accessing financial support and unexpected family events. Therefore, this needs to be considered both in terms of accuracy of the data and ethical use of PLA as an instrument of measure. Further, is it data for the good of the student or the organisation? EAI strives to improve individual student success, but also it has a role in improving retention which in turn benefits the organisation. The OU’s approach to using PLA is to use and apply information strategically (through specified indicators) to retain students and to support them to achieve their pathway goals. At a macro level, this (from an organisational level) is addressing student learning experiences and is used to inform strategic priorities that will improve student retention and progression; and at a micro level it uses analytics to drive short, medium, and long-term interventions to support (individual) student success (Open University, 2014).

Understanding the implications of how we use student data, and the ethics of PLA has raised some significant dilemmas which needed to be addressed and which have influenced the research design of this study resulting from outcomes of the pilot study where concerns were voiced about how far students were aware that we used their data...
to make predictions of their outcomes and how ALs should discuss this with students (Chapter Three Section 3.4). Another implication arising from the review of the ethics of using student data led to finding out how ALs use this potentially powerful information and whether holding knowledge brings with it a duty or responsibility to act on it and if so, how this is done ethically and with student achievement as the focus.

Having addressed the literature informing the ethical use of PLA, the chapter now moves forward to present literature that informed the conceptual and methodological understanding of the research, in particular the theoretical models that informed the research questions, the design of interview instruments and data interpretation.

### 2.5 Theoretical Models

While PLA is a relatively recent phenomenon, there are nearly four decades of research on how people accept, adopt, and use new technologies (Davis, 1989; Davis, et al., 1989; Venkatesh and Davis, 2000; Venkatesh et al., 2003).

Three major theoretical frameworks were chosen and reviewed for this research: The Theory of Planned Behaviour (TPB) (Ajzen, 1991), the Decomposed Theory of Planned Behaviour (DTPB) (Taylor and Todd, 1995) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, et al., 2003). Where TPB and DTPB look at behavioural intention in a more general sense, UTAUT is more specific to technology acceptance and has developed from early models of the Technology Acceptance Model (TAM) (Davis et al., 1989) and the Extended Technology Acceptance Model (more commonly referred to as TAM 2) (Venkatesh and Davis, 2000). UTAUT also incorporates elements of TPB (Ajzen 1991). Through the literature review, it was possible to see what part these models would play in informing the research design and developing a PLA-specific model which would help to address the proposed research questions (RQs).

Because this study aims to address ALs’ beliefs, technology use and data literacy, and actual usage about using PLA (RQs 1 and 2), it was important to have a measure of behaviour intent and actual usage with a clear evidence-based framework within which to analyse the findings. It is however noted that, while existing frameworks informed my understanding of how RQs could be answered, they did not limit or bound the data collection and analysis as to what those models indicated about adoption and use of technology. Interview analysis allowed for new insights to emerge and document any information the models did not capture, and which were specific to PLA use by teachers. This resulted in an elaborated understanding of PLA informed by both existing theory and emerging data. Choosing theoretical models was very much a case of balancing too much with too little regarding which would be the most appropriate for the research. Each model has developed and redeveloped over time and consequently decisions had to be made based on how useful to this research they would be.
2.5.1 The Theory of Planned Behaviour

TPB (Figure 8) is a social cognitive model and a theoretical approach which helps to understand behaviour in different settings. It is an extension of the Theory of Reasoned Action (TRA) (Ajzen, 1991; Fishbein and Ajzen, 1974). Both TPB and TRA emphasise the importance of an individual’s intention to perform an action, the level of motivation they hold, and how prepared a person is to work accordingly to achieve the behaviour. TPB suggests that the harder someone is willing to try, the more likely it is that a behaviour will be carried out (Teo, 2009). Other influential factors on intention are whether the resources needed to carry out a behaviour are available; whether a person holds the required skills to complete the behaviour and whether they are acting on their own indicators of intention. TPB looks also at the attitude towards a behaviour and the degree to which a person views the behaviour as favourable or otherwise. For understanding ALs’ use of EAI this is a key issue as there is evidence of low use or passive participation (as found by Herodotou et al., 2017; Herodotou et al., 2019a) and requires more exploration. TPB also addresses the subjective norm which is the perceived social pressure to perform or not to perform the behaviour.

For ALs there are potential influences which might impact on their decision to use EAI (for example, desire to please managers, fear of redundancy, or the personal need to demonstrate performance and acceptance). Conversely, the intention not to perform could come from other influences (for example trade union directive to work to existing contract agreements). Thirdly, it is perceived behavioural control; the ease or difficulty of performing the behaviour (for example teacher beliefs around past experiences, teacher training and perceptions that EAI is complex or time-consuming). According to Ajzen (1991) the more favourable the attitude and subjective norm and the greater the perception of behavioural control are, the more likely the person is to carry out the proposed behaviour.
2.5.2 Figure 8. The Theory of Planned Behaviour Model

Figure 8. Theory of Planned Behaviour Ajzen, (1991).

Ajzen (1991) argued that the beliefs relevant to the behaviour are also indicators of the intention to carry out an action. Behavioural beliefs are formed based on attitude towards the behaviour and whether the necessary resources and opportunities exist; the more resources and opportunities available, the greater the likelihood of successfully carrying out the behaviour. Normative beliefs are those which shape the subjective norms (social influences). It is suggested that the approval of others (peers, management) is key to performing a given behaviour and that the strength of these beliefs is multiplied by the person’s motivation to comply with the beliefs of others. Control beliefs are the perception of the level of control one has over the behaviour. Whilst it is recognised that one can hold a significant number of beliefs; it is argued by Ajzen that only a relatively small number of these can be acted on at a given time.

2.5.3 Criticisms of the Theory of Planned Behaviour from Education Studies

To implement technological changes there is a need to recognise how teachers will react according to their existing beliefs (which may prove to be more challenging to some more than others) (Westberry et al., 2015). Whilst there are studies that show efficacy using the TPB, there are also those which criticise its usefulness as a theoretical model to explain intentions where technology is used.

TPB can be useful in explaining teachers’ intentions to use technology generally, but it also has some limitations such as, for example, the intentions can more complex than the model supports (Teo, Zhou and Noyes, 2016). Other influences including personal characteristics, the organisation’s structure and how achievable the task is, are not well determined by TPB (Teo, 2009), suggesting that it works well as a generic framework across various disciplines, but in relation to education and technology use, it may present limitations. To address this limitation, additional models were reviewed including the
DTPB and UTAUT that provided a wider approach to the possible indicators of non-acceptance of technology.

2.5.3.1 Educational Studies Using the Theory of Planned Behaviour

In educational research using TPB, Sadaf and Johnson (2017) carried out a study to ascertain teachers’ beliefs about integrating digital literacy into the classroom. Their study was based on surveys among 50 (N=50) in-service teachers with six (n=6) follow up semi-structured interviews. Participants were across early years, middle and high school. They found that integration of technology depended primarily on the teachers’ behavioural beliefs about the value of digital literacy; how far they believed the behaviour would lead to a positive outcome (Ajzen, 1991). 80% of participants thought it developed 21st century skills, 62% felt it improved student engagement and 32% thought it prepared students for careers. Normative beliefs about how far others influence behaviour indicated that meeting the expectations of administrators was most influential at 84% whereas meeting the expectations of students was only 40%. The perception they held about the technology and their control beliefs indicated that having access to appropriate support resources (78% of participants) was the main driver in their use of digital literacy.

Also using TPB, Sugar, Crawley and Fine (2004) examined the technology beliefs of six (N=6) high school teachers. They carried out semi-structured interviews following on from a questionnaire to ascertain beliefs about including technology into their practice. Results indicated that technology adoption decisions were influenced by teachers’ individual attitudes towards the use of technology based on their personal beliefs about the consequences of its use. In this study subjective norms were not significant in teachers’ decisions to use technology. Lee, Cerreto and Lee (2010) carried out a study with 34 (N=34) middle and high-school teachers to ascertain their beliefs about the use of presentation software. Findings indicated that attitude was the strongest determinant of intention to act (being twice as important as subjective norms and three times as important as perceived behavioural control). These findings indicate that teachers’ decisions about technology use are primarily influenced by whether they view it as being of value, the opinions of influential others are moderate determinants, and perceived ability of use, is of less significance.

2.5.4 Decomposed Theory of Planned Behaviour

Building on TPB, DTPB (Figure 9) was developed by Taylor and Todd (1995) adopting elements from TPB and elements of TAM which introduces more specific technology use such as perceived usefulness (PU), and perceived ease of use (PEOU). In TAM, Davis et al. (1989) postulated that the use of any computer technology system can be determined by behavioural intention to use. This is viewed as being jointly determined by the person’s attitude toward using the system and perceived usefulness (Davis et al., 1989). The latter
is defined as ‘the degree to which a person believes that using a particular system would enhance his/her job performance’ (Davis, 1989, p. 320). Like DTPB, TAM also addresses intention but does so specifically in relation to the use of technology. As with DTPB it assumes that people act on their own volition so there is no question of coercion to act. TAM in its original form recognised that attitude and intention are determinants of behaviour, but that external constraints are also factors.

As well as incorporating determinants from TAM alongside TPB, DTPB also included the determinant of compatibility which is defined as ‘the extent to which [an] innovation is perceived as consistent with existing values, past experiences, and needs of potential users.’ (Rogers, 1995 cited in Eastin, 2002 p.252) The premise being that people are more likely to adopt an innovation (technology) that they are comfortable with and that is compatible with other technologies they already use (Eastin, 2002). DTPB also incorporates psychological determinants from TPB (subjective norms e.g., peer influence and superiors’ influence) which can also be seen as the influences of the organisational structure). It also adds self-efficacy which is based on social cognitive theory where consideration is taken of an individual’s belief in their ability to achieve their goal (Bandura, 1982; Bandura and Adams, 1977). There are two components regulating self-efficacy: (a) the efficacy outcome and (b) the self-belief that success will be achieved i.e., the efficacy expectancy of one’s own estimate that success will be achieve at the expected level (Gavora, 2010). Bandura (1982, p. 127) identifies four sources of self-efficacy: 1) Enactive attainments, where the successful completion of a task increases self-efficacy, or conversely, lack of success in achieving a task reduces self-efficacy. 2. Vicarious experience, where observing others achieving their personal goals increases self-efficacy. 3) Verbal persuasion, used to persuade someone that their self-efficacy is achievable. 4) Physiological state, when a person is in a steady physiological state, they are more likely to have higher self-efficacy whereas a heightened physiological state reduces self-efficacy.

Where TPB focuses primarily on the individual and their adoption of a behaviour, in DTPB Taylor and Todd (1995) also acknowledged that from an organisational perspective it is important to have the necessary resources available to support the use of technology and they argue that adding these more comprehensive determinants leads to a better understanding of user intentions. Thus, moving responsibility from purely the individual to also addressing the role of the organisation.
2.5.4.1 Criticism of the Decomposed Theory of Planned Behaviour

Where other studies have looked at the advantages and disadvantage of both TPB and TAM, Mathieson (1991) carried out a study of university students to ascertain their intentions to use information systems drawing on both TPB and TAM. Mathieson found that whilst both models were strong, TAM was more generalised and TPB was more comprehensive, thus using a combination of both models to develop DTPB for empirical studies was found to be effective. However, Ajzen (2011) (while accepting that variants can be successfully added) cautioned against utilising additional predictors to TPB without considering whether they are: specific to the behaviour; have a direct causal link to determining intention; that they are independent of existing determinants; and they are consistently proven to determine intention or behaviour through rigorous empirical studies. In criticism of this, Sniehotta, Presseau and Araújo-Soares (2014) argued that the fact that variants are added, is indicative that the TPB alone is not providing sufficient explanation of human behaviour and intentions in some situations.

2.5.4.2 Educational Studies using the Decomposed Theory of Planned Behaviour

Using DTPB, Shuie (2007) studied teachers’ use of instructional technology using path analysis to examine factors that influence teachers’ use of this. The study used self-reported data from 242 (N=242) science teachers. Shuie’s findings suggest that teachers’ attitudes and intentions toward using instructional technology were mostly determined by ease of use, perceived usefulness, and computer self-efficacy. They use self-efficacy as a
determinant but align it with technological responses (by applying it directly to computer use), rather than with psychological responses despite its origins in social cognitive theory, with subjective norms having only limited influence over attitudes and intentions. Addressing the TPB, TAM, and DTPB, they argued that ‘teachers’ use of instructional technology is influenced by a ‘tangled web’ of determinants rather than a few simple causal paths as the models suggest (Shui, p 441). From anecdotal evidence, this may go some way to explaining ALs’ attitudes to some degree i.e., what they understand from EAI visualisations and how confident they are that this understanding is correct (RQ3).

2.5.5 The Unified Theory of Use and Acceptance of Technology

The theoretical model of UTAUT suggests that the actual use of technology is determined by behavioural intention. The perceived likelihood of adopting the technology is dependent on the direct effect of four key constructs; performance expectancy (PE); effort expectancy (EE); social influence (SI); facilitating conditions (FC) (Venkatesh et al., 2003) Figure 10. Like DTPB, UTAUT addresses the acceptance of technology from both the perspective of the individual and the organisation. It also considers factors such as age and gender which are not specially addressed in TPB or DTPB.

**Figure 10. The Unified Theory of Acceptance and Use of Technology Model**

Performance expectancy (PE) is the degree to which an individual perceives that using a system will help them in their job performance. It recognises that both gender and age are significant factors relating to an individual’s PE. Research which focuses on gender differences suggested that performance expectancies, which focus on task accomplishment, are likely to be more relevant to men than women (Venkatesh et al., 2003). However, Kim et al. (2017) suggested that traditional societal gender roles are also influenced by age. Venkatesh et al. (2003) postulated that this still linked to gender because women enter the workforce at different stages of life according to other responsibilities such as family and childcare. The OU is an institution which may
challenge these assertions as the online distance working nature of the AL role is often associated with being a mode of work which is accessible to homemakers as it is possible to work flexibly to meet other responsibilities such as caring.

Effort expectancy (EE) is the extent to which the user perceives the system as easy to use and how this will impact on behavioural intention. This construct was recognised as perceived ease of use (PEOU) in TAM. Venkatesh and Morris (2000) suggest that EE is more relevant to women than to men. They also argued that the constructs related to EE are stronger determinants of individuals' intention for older workers due to increased difficulty in processing complex stimuli.

Facilitating conditions (FC) are the degree to which the user believes that the organisational conditions and readiness are adequate for effective use of the system. This construct relates to perceived behaviour control in the extended TAM. Once the technological and/or organisational environment remove any barriers to use, the FCs are ready.

Social influence (SI) is the degree to which the user perceives that others (who are important to the user) believe that they should use the system. The construct was represented as subjective norms in the extended TAM and is a construct whereby behavioural intention is based on the voluntary decision to use the system (voluntariness). Venkatesh et al. (2003) suggested that women tend to be more sensitive to others' opinions and therefore find social influence to be more relevant when forming an intention to use new technology until they become more experienced in its use. Older workers are also more likely to place increased emphasis on SI, with the effect declining with experience (Venkatesh and Morris, 2000).

In later iterations UTAUT was modified to create UTAUT 2 (Venkatesh, Thong and Xu, 2012) (Figure 11) by adding three additional constructs, 1) Hedonic motivation which is the fun derived from using technology which is considered to play a part in technology acceptance (Venkatesh et al., 2012). 2) Price value. Venkatesh et al., 2012 argued that when technology is used by employees in organisations, users do not feel responsible for the cost that is associated with the use of technology as they hold no responsibility for this. The intention to use is thus based on whether the user perceives the benefits of the technology outweigh the financial costs 3) Habit, which is the extent to which people perform behaviours automatically (Venkatesh et al., 2012).
2.5.5.1 Educational Studies using UTAUT

Radovan and Kristl (2017) carried out a study of an online HEI to address teacher acceptance and use of learning management systems (LMS) using the Community of Inquiry framework (Garrison, Anderson and Archer, 2001). The determinants of UTAUT (Venkatesh et al., 2003), were used to identify the main indicators of an e-learning environment for teachers and how teaching presence was influenced by the frequent use of online learning environments within the University of Ljubljana. The sample included 326 (N=326) teaching staff, 51% male and 49% female respondents. Most respondents were between 31 and 50 years old (59%), and between 41 and 50 years (30%). Respondents over 60 years old made up 9% of the sample and respondents younger than 30 years made up 10%. The purpose of the study was to examine how acceptance and use of a learning management system among teachers influenced their approaches to teaching online. The findings of this study indicated that using UTAUT, PE, showed that the usefulness of the management learning system was the main indicator of technology acceptance. The stronger the usefulness was, the stronger the intention of teachers to use it. However, Radovan and Kristl (2017), found that EE was not a major determinant, which they assumed was because the LMS being used was intuitive, plus the teachers’ level of technology expertise was already high. FCs were influential on the behavioural intention and SIs had some impact on acceptance of the LMS but did not influence its actual use. To summarise, findings showed that social environment and PEOU increased the PU of LMS. From their study, behavioural intention appeared to be a good predictor of actual use insofar as the more a teacher liked using the LMS, the more inclined they were
to use it. This finding is congruent with other empirical UTAUT studies (Lee et al., 2010; Venkatesh et al., 2003).

In further educational studies Chao (2019) carried out an online survey with 1,562 (N=1,562) students to identify factors affecting students’ behavioural intentions of using mobile learning. They used UTAUT with the addition of perceived enjoyment, mobile self-efficacy, satisfaction, trust, and perceived risk moderators. Results showed that perceived satisfaction and perceived enjoyment were the main drivers influencing students’ behavioural intentions towards using mobile learning. PE and EE along with trust were also influencers for behavioural intention to use mobile learning.

Using UTAUT, another study from the OU was conducted to prompt ALs to use the EAI dashboard at regular milestones in a student’s study journey. Using a convergent parallel design, including 11 (N=11) semi-structured interviews plus log file data, Herodotou et al. (2021) looked specifically at ways to improve the passive resistance to using EAI by sending ALs email reminders prompting them to look at the dashboard. The participant sample was taken from OU business and law modules. The emails were initially sent to managers, who then sent them to ALs to identify students in need of support prior to the next assignment submission date. ALs were asked to check the data to identify student needs and act accordingly. Findings indicated that email reminders influenced systematic engagement for some ALs, who recognised the value of using EAI alongside existing teaching strategies to provide timely support, as well as increasing their habit of checking the data regularly. There was also some scepticism regarding the value that EAI added to existing teaching strategies given that some ALs already had experience of managing students at risk. There was also some scepticism around how predictions were generated (also discussed in Section 2.4.4).

2.5.5.2 Criticisms of UTAUT from Educational Studies

Radovan and Kristl (2017) argued from their study that because UTAUT is used to predict the acceptance of different technology, it did not fully address the use of e-learning and therefore to fully understand the issues, it would need to be supplemented with more factors aligned to education. They found that there were variances which were unexplained, therefore more research was needed to identify these influences. Similarly, Chao, (2019) stated that further external variables would improve UTAUTs ability to predict the acceptance of technology noting that other research has included variables such as self-efficacy, perceived risk, trust, habits, and satisfaction. Some of these variables exist in other models, for example, self-efficacy is a variable in DTPB. Chao (2019) therefore argued that UTAUT alone does not have the capability to explain individuals’ technology acceptance as the variables proposed are too limited. Therefore, an extension to UTAUT by adding the variables mobile self-efficacy, perceived enjoyment, satisfaction, perceived risk, and trust would be more useful to predict behavioural intention
regarding e-learning. Suggestions by Chang et al. (2017) who carried out a study of 714 (N=714) undergraduate and masters students using a convenient sampling technique identified the importance of enjoyment which they argued is generally overlooked in studies. Khalilzadeh, Ozturk and Biliğihan (2017) further stated that trust is a crucial factor determining users’ behavioural intentions to adopt technology.

### 2.6 Comparing the Models

In summary, TPB emphasises the importance of the determinants which lead to intention to carry out a behaviour. It focuses on motivation and how hard one is prepared to work to achieve the behaviour. It recognises that attitude, social norms, and perceived behavioural control are the influential determinants in predicting intention with behavioural, normative, and control beliefs influencing the attitude one holds towards intention and focuses on the individual behaviour rather than external factors such as organisational readiness to support the intended actions of the behaviour. Evidence from this literature review indicates that there are education studies to support its validity as a model for understanding teacher use of technology noted by Lee et al., 2010; Sadaf and Johnson, 2017; Sugar et al., 2004 (Section 2.5.1.2). However, there is also evidence that there are limitations noted by Teo, Zhou and Noyes (2016) and Teo (2009) (Section 2.5.1.1).

DTPB has developed to form a variant of the TPB which also addresses the use of technology more specifically and how PU and PEOU and compatibility of the technology will influence attitude towards behavioural intention and usage. Rather than using beliefs, the focus is on self-efficacy (Bandura 1982). Education studies indicate that using a combined model has mixed results, as Shui (2007) suggested that understanding technology use is more complex than simple causal paths, whereas Teo et al. (2016) suggest that the addition of the TAM determinants of PU and PEOU balances the problem of subjective norm being the weakest indicator of intention. The determinants added to TPB by DTPB strengthen the model and particularly when considering self-efficacy, peer influence and superior (or organisational) influences.

UTAUT has since considered social norms as determinants of intention (Venkatesh and Davis, 2003). However as cautioned by Bagozzi (2007) adding more determinants does not necessarily lead to its improvement but moreover it may reduce its strength. However, UTAUT provides a more comprehensive address of both individual behaviour toward technology acceptance with the recognition of the potential influences of age and gender. It also addresses the organisational structure by looking at the facilitating conditions. UTAUT 2 adds the determinants hedonic motivation, price value and habit.

### 2.6.1 Theoretical Models: Implications for This Study

One of the limitations of this thesis which has been identified from this literature review is that most frequently, it is quantitative studies which use the theoretical models chosen and
therefore, the range of studies discussed do not necessarily reflect the mixed methods approach taken in my research. However, as identified by Renzi and Klobas (2008) some researchers choose to use quantitative methods when the data availability dictates it. Similarly, Ajzen (2002) stated that qualitative data plays a role when the objective is to prompt an understanding of beliefs which can be better addressed through direct questioning. Renzi and Klobas (2008) conducted 26 (N=26) semi-structured interviews with university lecturers using TPB to explore the use of e-learning platforms. Using this approach, they were able to identify differences in the attitudes, social influence, and perceived behavioural control among three identified areas of e-learning: They argued that using qualitative data they were able to identify data patterns showing differences among the teachers who adopted different teaching models. A further example of a qualitative study using UTAUT was carried out by Gruzd, Staves, and Wilk (2012) who conducted 51 (N=51) semi-structured interviews with students to investigate how they integrated social media into their personal and professional lives. They acknowledged that using UTAUT when conducting semi-structured interviews was uncommon, but they were keen to investigate the appropriateness of using UTAUT for conducting research in this field. Gruzd et al. (2012) successfully identified that UTAUT constructs useful for studying the behavioural intention and use of social media amongst students.

Addressing the theoretical models was a first stage in understanding the complexities of the attitudes, beliefs, and intentions of using technology in education which could then form a basis for applying theory to this thesis. TPB addresses attitudes beliefs and intentions but while subjective norms address some of the more psychological and social feelings relating to choices of behaviour, it is limited in its application for this research as it does not specifically address technology use. DTPB takes up some of these limitations focusing on both individual behaviour and technology use as the determinants of PU and PEOU specific to technology use with the addition of self-efficacy. UTAUT further adds the more technology-based determinants which is fundamental for this research. While UTAUT 2 adds additional determinants, UTAUT in its original format was chosen as a theoretical framework for this research as the additional determinants of UTAUT 2 (price value, hedonic motivation and habit) are less significant for educational studies. To this end this research will use the theoretical models of TPB DTPB and UATUT as determinants to inform the research design and methodology.

Table 1. List of determinants from relevant model to explain use of technology acceptance and behavioural intent

<table>
<thead>
<tr>
<th>Determinants</th>
<th>TPB</th>
<th>DTPB</th>
<th>UTAUT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Behavioural beliefs</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Normative beliefs</td>
<td>X</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 1. List of determinants from relevant model to explain technology acceptance and behavioural intent.

<table>
<thead>
<tr>
<th>Control Beliefs</th>
<th>X</th>
</tr>
</thead>
<tbody>
<tr>
<td>Performance expectancy</td>
<td>X X</td>
</tr>
<tr>
<td>Effort expectancy</td>
<td>X X</td>
</tr>
<tr>
<td>Compatibility</td>
<td>X</td>
</tr>
<tr>
<td>Peer Influence</td>
<td>X X</td>
</tr>
<tr>
<td>Superior’s influence (Organisational influences)</td>
<td>X</td>
</tr>
<tr>
<td>Self-efficacy</td>
<td>X</td>
</tr>
<tr>
<td>Resource facilitating conditions</td>
<td>X X</td>
</tr>
<tr>
<td>Technology facilitating conditions</td>
<td>X X</td>
</tr>
<tr>
<td>Attitude</td>
<td>X</td>
</tr>
<tr>
<td>Subjective norm/Social influences</td>
<td>X X X</td>
</tr>
<tr>
<td>Perceived behavioural control</td>
<td>X X</td>
</tr>
<tr>
<td>Behavioural intention</td>
<td>X X X</td>
</tr>
<tr>
<td>Experience</td>
<td>X</td>
</tr>
<tr>
<td>Voluntariness</td>
<td>X</td>
</tr>
<tr>
<td>Gender</td>
<td>X</td>
</tr>
</tbody>
</table>

2.7 Conclusion

This Chapter has identified three phases of literature review to inform this research. Firstly, it has addressed the ongoing wider studies relating to PLA and the more applied OU studies of using EAI. Secondly, it has acknowledged that there are implications for the use of PLA which create potential barriers to its use though the ethical concerns around how student data is used and the trustworthiness of PLA data. Thirdly, seminal works relating to theoretical models have been considered to inform this research into understanding of teachers’ attitudes and intention to use PLA.

From this literature, gaps in areas yet to be considered have emerged, including understanding the reasons why the adoption of EAI use is relatively low, (despite the fact that at the briefing sessions I delivered the attitude towards its usefulness was overwhelmingly positive), the need to address the ethical use of student data and how this may relate to teachers’ attitudes and
actual use of PLA, and how organisational structures may relate to use and adoption. Whilst there is a comprehensive field of work developing in this area on which this thesis will build (Herodotou et al., 2016; 2017; 2019a; 2020a; 2020b; Hlosta et al., 2017; 2020; Kuzilek et al., 2015; Rienties et al., 2016a; 2020) further investigation is needed to gain a better and in-depth understanding of the reasons why teachers’ interest does not necessarily lead to them using PLA.
Chapter Three Methodology

Chapter Two has evaluated the body of work in the field of Predictive Learning Analytics (PLA), ethical considerations, and the role that theoretical models have played in informing the research questions (RQs) of this research. Chapter Three now moves forward to look at the chosen methodology which has evolved and developed from the literature review to address the following RQs:

1) How do existing teacher beliefs influence Associate Lecturers’ use of PLA?
2) How does knowledge of (a) technology and (b) data literacy relate to Associate Lecturers’ use of PLA?
3) What are Associate Lecturers’ (a) perceptions of the use and usability of PLA and (b) actual use as measured by fine-grained eye-tracking approaches and observation of use?

The philosophical underpinnings in Section 3.2 discuss the rationale of taking a phenomenological approach in this thesis, and its relevance for hearing and understanding the experience of participants in using the Early Alert Indicators (EAI) dashboard. It also addresses the advantage of taking a pragmatic stance to enable a more diverse approach to include both positivist and realist perspectives. Section 3.3 discusses the study setting and the unique role of Associate Lecturers (ALs) and students at the Open University (OU). It then clarifies the findings of the initial pilot study carried out in 2018 in Section 3.4. Section 3.5 outlines the process of participant selection and their demographics. Section 3.6 discusses the data collection instruments:

- Study One: Semi-structured interviews.
- Study Two: Eye-tracking in conjunction with Retrospective Think Aloud Protocols (RTAP).
- Study Three: Screen-sharing in conjunction with Concurrent Think Aloud Protocols (CTAP).

Section 3.7 addresses the methods of data analysis and the decision basis for using a thematic analysis approach to analyses qualitative data and Tobii Studio software eye-tracking metrics for collection of quantitative data. Section 3.8 outlines the ethical challenges of the research process before concluding the Chapter with Section 3.9.
3.1 Philosophical Underpinnings

Understanding the philosophical position of research is the starting point for developing a systematic and identifiable rationale to facilitate meaningful interpretation of the research process. It provides a basis for defending your position as a researcher and the basis for interpreting meanings, values, opinions, and experiences of others. As discussed by Jackson (2013), clarity of philosophical stance allows for informed choices to be made regarding the methodology and the methods to be used. Researchers must acknowledge how their own position, knowledge, and assumptions impact on all aspects of the research from the development and design to data collection and interpretation of findings. It demonstrates a sound basis for interpreting the meanings, values, experiences, opinions, and behaviour of other people (Jaye, 2002). In Section 3.2.1 below, phenomenology is discussed with a rationale for this position, followed by a discussion to adopt a pragmatic approach (Section 3.2.2). Figure 12 below summarises the process.

Figure 12. Overview of the Research Rational

![Diagram of research rationale]

3.1.1 Phenomenology

This research has adopted a phenomenological approach based on the work of German philosopher Husserl, who developed a theoretical framework to demonstrate how knowledge becomes a reality. A phenomenological researcher is thus interested in describing the lived experience as a person sees it, rather than interpreting this from the researcher's perspective (although inevitably there is an element of researcher interpretation of the findings) (Bevan, 2014). Phenomenology investigates ‘the experience of participants from an empathetic and open perspective, but also takes
account of the researchers’ assumptions’ (Butler-Kisber, 2010, p. 52). It is a basis for understanding people and how they make sense of their world and their reality, it draws on the principle that to understand human relationships we must understand and apply the ‘concepts of empathy, openness and participation in how we approach data collection’ (Butler-Kisber, 2010, p. 52). It is self-critical insofar as it continually examines its goals and the validity of the methods (for example strengths and limitations) used to carry out the research study (James and Busher, 2009).

In a phenomenological approach, participants are fully active in the research process. Each participant will interpret the meaning they ascribe to a question in a different way, and this allows for a thorough and methodical investigation of a problem using qualitative methods (Bevan, 2014). Of the participants who have taken part in this research, each has different beliefs towards using the EAI dashboard, based on factors such as their faculty support, and their level of teaching experience both in the OU and other education institutions, and their personal experience of using technology at home and at work. Full activity in the research process was achieved by framing a semi-structured interview question protocol which specifically explored these phenomena. Participants were able to discuss their beliefs and perceptions of the usefulness and the usability of the EAI dashboard through self-reporting. In the eye-tracking study, the RTAP interview questions allowed for a less structured but individually focused account of the use of the EAI dashboard and the screen-sharing study. CTAP interview questions (which were less nuanced than the eye-tracking but nevertheless added depth to the findings) allowed for free-flowing discussion of the use of the dashboard as it happened.

3.1.2 Pragmatism

Whilst the framework of phenomenology is central to understanding the AL experience of using PLA, it is limited as a sole approach, due to the need to address the quantitative aspects of the research and the positivist theoretical models which are being used to support the rationale for the study. Understanding the theoretical concept of pragmatism has been a key factor in the process leading to the use of mixed methods and making decisions on how to move forward taking account of the changes to the research from the pilot study (Section 3.4). One of the reflections leading to a reconsideration of the research was listening to and developing learning from feedback. Feedback from the initial study identified that as a researcher, I took a realist standpoint, but that the theoretical models I used to underpin my research (Chapter Two) were mainly from a positivist perspective. Many of the studies discussed in the literature review, addressed technology acceptance among teachers (making and testing hypotheses from existing theoretical models of technology use and acceptance) and were based primarily on quantitative studies. For this research the theoretical models were used as a starting point
to help in framing the understanding of ALs’ beliefs and perceptions of using the EAI dashboard and to provide a framework for RQ1 and RQ2. To link these to a phenomenological approach research questions were designed using the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), The Theory of Planned Behaviour (TPB) (Ajzen, 1991) and The Decomposed Theory of Planned Behaviour (Taylor and Todd, 1995) allowing participants to describe their own experiences while having a framework to ensure that the interview questions were focused on the RQs (Appendix 2).

As part of the research design, understanding and unpicking my own belief system was central and I needed to fully understand my ontological and epistemological beliefs. Ontology is the assumptions we make about the nature of reality and epistemology is our beliefs about how we find out about that reality. Ontology is a theoretical stance which defines two main assumptions a) Realist; that there is one objective reality of life. b) Realism; the belief that there are multiple realities which can be uncovered through subjective exploration and understanding of the lived experience (Twining et al., 2017). Epistemology refers to the belief and scope of knowledge and how we view the world. If a relativist (objective) ontology is adopted, the epistemological position would suggest that there is one true answer to the knowledge sought, whereas a realism (subjective) ontology suggests that meaning is socially and culturally constructed, with multiple truths (Twining et al., 2017).

My own ontological position remains that of realism and the belief that, as teachers, ALs will have different approaches to how they support students. Epistemologically, my position is that these different experiences will be best discovered through exploring a range of explanations to uncover the meanings participants give to their experiences of using EAI.

Pragmatism is also a deconstructive approach which advocates for the use of mixed methods in research, allowing for the use of the methods which appear best suited to the research irrespective of whether they are quantitative or qualitative (Feilzer, 2010). Using a pragmatic approach therefore rejects the idea that a researcher must choose their position be it constructivism, positivism, or realism (Tashakkori & Teddle, 2002).

According to Creswell (2009) pragmatists link their choice of approach directly to the purpose of, and the nature of the research questions posed, thus allowing for the freedom to use methods that are the most appropriate for their value base. Pragmatism draws on the importance of warranted beliefs; the concept that repeating similar actions in similar situations shapes the consequences of the action which then leads to a better conclusion (Morgan, 2017). In pragmatism, the assumptions associated with realism, constructivism or positivism do not pose questions about combining qualitative and quantitative methods, therefore, it is not necessary to believe in the existence of an external reality to do a
questionnaire nor is a need to deny the existence of truth if you carry out interviews (Morgan, 2017).

In this research I wanted to gather a deeper understanding of a range of areas. Firstly, I wanted to know the general beliefs held about using PLA as a teaching tool. (RQ1). Secondly, I wanted to investigate the relevance of knowledge of data and use of technology in general and whether this influenced PLA use (RQ2). Thirdly, to add validity and depth of understanding, using eye-tracking allowed for a fine-grained understanding of actual use (RQ3). By applying metrics, we could see how usage compared across participants and across the actual dashboard functions and identify any misconceptions or anomalies in actual use.

According to Morgan (2017), it is likely that qualitative researchers will rely on realist ideology and quantitative researchers will rely on positivist assumptions. Adopting a pragmatic approach for this research allowed for the freedom to draw on the models discussed in the literature review to inform the research. It was still possible to use the perspective of phenomenology to draw on participants’ lived experience; feelings, thoughts (and sometimes frustrations) when using EAI without rejecting my realist standpoint, whilst from a positivist position, I could use the knowledge gained from factual information gathered from the eye-tracking data (RQ3).

Smith (1983) summarised three specific indicators as to whether quantitative or qualitative methods are most appropriate for a research study: 1) The relationship of the researcher to what is being investigated: Quantitative research separates facts and values whereas qualitative research sees these as being inextricably linked. Quantitative research therefore searches for a truth where qualitative research attempts to understand multiple realities. Deciding which method to use therefore depends on what the researcher seeks to investigate and their epistemological position. 2) The relationship between facts and values in the process of investigation: A quantitative approach seeks objectivity with minimal bias and uses a set of established procedures which prevents the researcher’s position from influencing the facts. The same result should be achieved if the method is used by others, therefore the researcher’s epistemological position should not influence the results. From a qualitative approach there is acceptance of subjectivity and the likelihood that the researcher and participant may share similar views. 3) The goal of investigation: because quantitative research focuses more on statistical analysis and constructing facts, its aim is to provide a complete, detailed description of the research topic. Qualitative research is usually more exploratory in nature and its aim is to understand a specific phenomenon through investigating the experiences of participants.
Choosing carefully between qualitative or quantitative methods is crucial therefore to ensure that the research is robust. In mixed methods research, quantitative and qualitative research methods, approaches, and concepts can be combined into a single study. Mixed methods research can therefore be used to improve data accuracy and to find data that might be missed using a single method (Baškarada and Koronis, 2018). In this research, using mixed methods meant that self-reports could be further validated by observation and discussion of actual use.

Using both quantitative and qualitative research data, allowed for depth of understanding and corroboration, which might otherwise be limited if only a single approach was used (Tashakkori & Teddlie, 2002). It is defined as a methodology that focuses on research questions that call for real life contextual understandings, and multi-level perspectives and ‘intentionally integrates or combines these methods to draw on the strengths of each’ (Creswell and Clark, 2011, p. 4). Mixed methods research requires a challenging level of expertise as there is a need to be familiar with both quantitative and qualitative methods which can lead to a complex research design which can be complicated to unpick, leading to advantages and disadvantages (Table 2). Palinkas et al. (2015, p. 543) suggested that ‘the promise of mixed methods, lies in its ability to move beyond the confines of existing methodological approaches and develop innovative solutions to important and complex problems.’

**Table 2. Advantages and Disadvantages of Mixed Methods Research**

<table>
<thead>
<tr>
<th>Disadvantages</th>
<th>Advantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Requires methodological expertise in multiple areas.</td>
<td>Using both quantitative and qualitative methods provides a more in-depth research design</td>
</tr>
<tr>
<td>The research design can become complex</td>
<td>Using both quantitative and qualitative methods leads to a higher level of integrity of findings</td>
</tr>
<tr>
<td>Can be difficult to plan and implement one method by drawing on the other</td>
<td>Results from one method inform the research process and implementation of another method (in this instance qualitative data inform quantitative methods)</td>
</tr>
<tr>
<td>It can be difficult to resolve discrepancies that arise in the interpretation of the findings using both quantitative and qualitative methods</td>
<td>Using both quantitative and qualitative methods can lead to findings that might not otherwise be discovered</td>
</tr>
<tr>
<td></td>
<td>Using both quantitative and qualitative methods develops the scope of the study by using different methods for different aspects of study</td>
</tr>
</tbody>
</table>

*Table 2. Summary of the main advantages and disadvantages of MMR based on Creswell and Plano Clark (2011).*
3.1.3 Mixed Methods: Qualitative

The essence of qualitative research is to build up a meaningful picture without compromising its richness and dimensionality. Qualitative research aims to seek answers for questions of 'how, where, when, who and why' with a perspective to build a theory or refute of an existing theory (Leung, 2015). Hammersley (2013) suggested that the research method selection is dependent on the circumstances and objectives of the research and should be driven by: 1) The research question: Research flowed from a realist position and an understanding that a phenomenological approach would be an appropriate approach to generating an understanding of the experiences of using the EAI dashboard among ALs. For some ALs the use of the EAI dashboard was sporadic so relying solely on memory could be problematic in defending the research and ensuring its validity. Hence, the decision to use a second method which allowed for observation would help to mitigate some of these concerns. 2) The existing body of research: As seen in Chapter Two Section 2.3.1 and Section 2.3.2, there is an existing field of work looking at the use of PLA for both students and teachers, however as noted by Bodily and Verbert (2017) and Jivet et al. (2017) systematic literature reviews have identified that research into PLA use is still in its infancy. So far there are no specific studies of PLA which have used eye-tracking observation as a method of data collection, therefore this research builds on and expands the existing body of work. 3) The available data: according to data from the Human Resources at the OU, as of December 2021 there are over 4,000 ALs working on undergraduate programmes across four faculties with access to the EAI dashboard (Table 3 Section 3.3).

The potential breadth of participants is therefore significant. One of the major assumptions preceding the study was that ALs are resistant to using PLA as supported by research findings in Herodotou et al., (2017; 2019a; 2020a) and discussed in Chapter Two. Despite a large number of individual ALs using the dashboard at the moment (1K+), the overall number of ALs is limited compared to the AL population at the OU (4K), with evidence of an all-time lower usage for 2020 – 2021 (Chapter One, Section 1.2.1).

3.1.4 Mixed Methods: Quantitative

Quantitative research focuses on quantifying the collection and analysis of data and is a deductive approach based on the testing of theory (Fetters, 2020). Therefore, where qualitative methods have allowed participants to give their own account of their experiences based on beliefs from their personal perspective, adding a quantitative element, has given scope to the analysis of statistical values alongside the observations and self-reports to identify the possible relationships between the qualitative and quantitative data adding a level of depth which might otherwise have been lost (QUALS
plus Quants). The quantitative findings are used to inform the qualitative and to add depth to qualitative themes.

Frequently, in quantitative research participants might be asked to complete a questionnaire which would then be numerically analysed using a statistical method such as the Analysis of Variance Model (ANOVA) which is a statistical test to identify differences between mean measure (Larson, 2008). It is however more commonly used for measuring groups against each other. Quantitative data are any data that are in numerical form such as statistics or percentages (Gray, 2018). In this thesis, it is the numerical collection of eye movements that formed the quantitative element. In using eye-tracking technology to view the EAI dashboard, where participants consistently focused on specific areas of interest (AOI), there was scope to reveal factors explaining use or non-use such as difficulty in processing information or particular interest in an EAI field. It also added clarity to exactly where participants showed the most interest. A scan path showed specific AOIs (the most looked at areas of the identified fields) and formed heatmaps (what was and was not looked at) and gaze plots (identifying sequences). From here it was possible to see whether certain AOIs were common among participants. Participants were able to freely use the EAI dashboard in whatever way they wanted. From this, gaps in their understanding could be identified and a picture emerged of the way in which the EAI dashboard was used via fine-grained observation of use. So far and to the best of my knowledge, PLA studies have not included observation through eye-tracking to understand teachers’ use of PLA. Thus, combined with self-reports, this research takes a novel approach. Firstly, it increases validity by supporting the qualitative data, secondly it adds a not yet used methodological approach to the existing stream of work in understanding teachers’ use of PLA higher education.

To understand the setting in which the research is situated, the next section moves forward to look at the study setting and particularly the unique demographic of OU ALs and students.

### 3.2 Study Setting: The Open University

The OU is a distance learning university where most students are studying from home, with some research students based on the campus in Milton Keynes. It is the largest university in the UK with the following faculties: Arts & Social Sciences; (FASS) Business and Law (FBL); Science, Technology, Engineering & Mathematics (STEM); Wellbeing, Education & Language Studies (WELS); Institute of Educational Technology (IET). ALs are responsible for teaching across all modules (courses), and many have professional working roles outside of the university. Unlike staff employed on campus in academic support or administrative roles, ALs are presently employed on a contract basis for each module taught, although full-time equivalent contracts allowing more security are being implemented from August 2022 onwards. In January 2021, there were 3.880 ALs in
employment on undergraduate programmes with 424 teaching across more than one faculty and therefore this is represented as higher figures in the faculty breakdown (Table 3). At the time of writing EAI was not available on post-graduate modules.

### Table 3. Number of ALs employed on undergraduate modules within each faculty

<table>
<thead>
<tr>
<th>Faculty of Arts and Social Sciences</th>
<th>1323</th>
</tr>
</thead>
<tbody>
<tr>
<td>Faculty of Business and Law</td>
<td>507</td>
</tr>
<tr>
<td>Faculty of Science; Technology; Engineering and Mathematics</td>
<td>1231</td>
</tr>
<tr>
<td>Faculty of Wellbeing; Education and Language studies</td>
<td>1058</td>
</tr>
<tr>
<td>PVC (Students) (Research only)</td>
<td>185</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>4304</td>
</tr>
</tbody>
</table>

*Table 3. Number of ALs in each faculty teaching on undergraduate modules at the OU Jan 2021. Source: Academic Services, the OU.*

Unlike campus-based universities, the OU is almost completely online. Some modules do periodically have face-to-face tutorials, usually held in other campus university buildings at weekends or in the evenings. Recently, due to Covid-19 all tutorials have been delivered online. Working at a distance can create unique challenges for teachers and students but it can also provide opportunities. Online distance learning is often characterised as a flexible mode of learning allowing for access to learning materials from anywhere and usually at any time (Sitzmann et al., 2006).

The OU also allows for the download of module materials in a range of formats, so it is possible to work offline if no internet connection is available and is popular with students who use travel time or time away from the computer screen to study. Asynchronous online environments (such as forums) allow students to study at their own time and fit around other responsibilities. Synchronous sessions (such as online tutorials) allow students to interact with student peers and tutors at defined times. Students can learn at their own pace provided they meet assessment deadlines, and the module materials are always accessible to review and revisit if necessary.

#### 3.2.1 The Open University Associate Lecturers (ALs)

For those ALs who are delivering undergraduate teaching, each is responsible for a student group of approximately 25 students, and some will teach on multiple modules.

The strength of relatively small tutor groups is that tutors know their students well, even though they may never meet in a face-to-face environment (Jelfs, Richardson and Price, 2009). Module materials are written by central academic staff. Generally, the module materials follow a similar online visual but with some variations according to the module needs. Students access their module materials via a home page (StudentHome) and are presented with a weekly calendar to follow the activities and module content. Students have access to tabs taking them to resources, such as; the Library and Tutorials, which link them to their online classroom for synchronous teaching; Forums, where they can
participate with other students and their tutor asynchronously on module content; Assessment, where they can access their assignment titles, deadlines, information about assessments in general (avoiding plagiarism, additional study materials to support academic writing) and an assessment submission link. Other web-links will take them to student support services, computer support and wider OU systems.

ALs are required to be available to work online and access the OU interface via a home page (TutorHome) where they have access to the module page and the tabs available to students. The tutor resources tab links them to additional teaching resources and a module forum for tutor discussions. Also, on the Tutorhome page, they can access wider OU systems. Information regarding their student group is available via this tab and demographic and study history of students is available along with any additional needs they might have (Figure 13). From here they can drill down to see more demographic information regarding individual students (Figure 14).

Figure 13. Information available to ALs regarding their tutor group of students

![Student group summary](image-url)

<table>
<thead>
<tr>
<th>Student name</th>
<th>PI</th>
<th>Module login</th>
<th>Allocation</th>
<th>TM1A</th>
<th>TM1B</th>
<th>TM2A</th>
<th>TM3A</th>
<th>TM3B</th>
<th>TM3D</th>
<th>Special circumstances</th>
<th>Update Record</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alice</td>
<td></td>
<td>17/03/2021</td>
<td>25/01/2020</td>
<td>82</td>
<td>85</td>
<td>92</td>
<td>85</td>
<td>Received</td>
<td>(RD)</td>
<td>Unstable Record</td>
<td></td>
</tr>
<tr>
<td>Bob</td>
<td></td>
<td>26/05/2021</td>
<td>25/01/2020</td>
<td>83</td>
<td>-</td>
<td>84</td>
<td>76</td>
<td>Received</td>
<td>(RD)</td>
<td>Unstable Record</td>
<td></td>
</tr>
<tr>
<td>Carol</td>
<td></td>
<td>25/01/2021</td>
<td>14/10/2020</td>
<td>71</td>
<td>68</td>
<td>73</td>
<td>68</td>
<td>Received</td>
<td>(RD)</td>
<td>Unstable Record</td>
<td></td>
</tr>
<tr>
<td>David</td>
<td></td>
<td>31/05/2021</td>
<td>25/01/2020</td>
<td>71</td>
<td>79</td>
<td>77</td>
<td>82</td>
<td>Received</td>
<td>(RD)</td>
<td>Unstable Record</td>
<td></td>
</tr>
<tr>
<td>Emily</td>
<td></td>
<td>16/06/2021</td>
<td>25/01/2020</td>
<td>82</td>
<td>88</td>
<td>87</td>
<td>72</td>
<td>Received</td>
<td>(D)</td>
<td>Unstable Record</td>
<td></td>
</tr>
<tr>
<td>Frank</td>
<td></td>
<td>26/05/2021</td>
<td>25/01/2020</td>
<td>75</td>
<td>68</td>
<td>86</td>
<td>86</td>
<td>Received</td>
<td>(D)</td>
<td>Unstable Record</td>
<td></td>
</tr>
<tr>
<td>Grace</td>
<td></td>
<td>24/05/2021</td>
<td>25/01/2020</td>
<td>72</td>
<td>74</td>
<td>82</td>
<td>80</td>
<td>Received</td>
<td>(D)</td>
<td>Unstable Record</td>
<td></td>
</tr>
<tr>
<td>Harry</td>
<td></td>
<td>02/10/2021</td>
<td>25/01/2020</td>
<td>64</td>
<td>62</td>
<td>71</td>
<td>76</td>
<td>Received</td>
<td>(RD)</td>
<td>Unstable Record</td>
<td></td>
</tr>
</tbody>
</table>

Figure 13. Information available to ALs regarding their tutor group.
Teaching at a distance is inevitably different to face-to-face teaching and so are student needs. Early studies from the OU by Jelfs et al. (2009) identified what is good tutoring in distance learning and they argued that working in distance education requires teachers to adopt different skills to campus-based teachers. An example included understanding students’ expectations of engagement regarding the time commitment for the level of study particularly as most OU students have other responsibilities and study may not always be their primary commitment. It also provides flexibility, for example, not being restricted by time and location (Lee and Choi, 2011). The flexibility of distance learning also allows students to work through their education while being employed or having other responsibilities at the same time. More recently due to Covid-19 teachers in universities have had to consider how to teach otherwise face-to-face courses using distance learning and develop distance teaching skills in a relatively short time. A recent study by Mendoza, Diaz, and Raffo (2021) identified that issues arose around students feeling part of a cohesive group and technological connectivity difficulties. These factors demonstrate that the skills needed to teach distance learning modules as identified by Jelfs et al. (2009) are still pertinent.

### 3.2.2 The Open University Students

Information from the Data and Student Analytics team at the OU (2021) showed that there were over 175,000 students enrolled at the OU and of these more than 7,700 were overseas students. The demographic has changed over the years to include a younger age group and over 34% of the new intake of undergraduate students in 2021 were under the age of 25 years. This is a demographic shift, as the OU has long been associated with
mature students. Reasons for this demographic shift are yet to be addressed, but the recent Covid-19 pandemic has created a situation where distance learning has become more attractive with more face-to-face Higher Education Institutions (HEIs) having to adapt their practice to deliver online education (Dhawan, 2020; Mendoza et al., 2021).

Students at the OU study module materials online or as a combination of online and printed sources and participate in a range of tutor-led online learning including regular tutorials, forums, pre-prepared activities as well as having email and phone contact with their tutors. As a distance learning institution, identifying students at risk, and offering the necessary support is potentially more challenging than at campus-based universities where students are more visible on a day-to-day basis (Herodotou et al., 2020a).

Distance learning students study in various places such as home, secure environments (prisons and secure hospitals) whilst traveling, and often in relative isolation, and even more so with the recent Covid-19 pandemic where face-to-face tutorials and day schools have moved online. Whilst ALs are experienced in recognising some of the warning signs that a student might be silently withdrawing from their studies, the overall retention at the OU is significantly lower than those of campus-based universities (Herodotou et al., 2020a). This is because the OU has an open entry policy meaning that students can register without formal qualifications. As identified by van Ameijde, Weller and Cross (2018) open entry criteria lead to much higher student withdrawal rates. They acknowledged that while there might be significant personal choices attached to this such as professional responsibilities, recognising that studying is not for them or having completed as much of their studies as they need to, there are also those for whom dropout is not an informed choice and with the right support the student could complete their studies. The requirement to improve student retention is evident in most HEIs. However, where students are learning at distance, the retention levels fall even shorter with the percentage of students not completing their degrees having been as high as 78% (Simpson, 2013).

In a systematic literature review of 40 studies between 2010 and 2018 of online courses, Muljana and Luo (2019) found that despite student demand, the retention rates were significantly lower than those of campus-based courses indicating that the low retention rate of students at the OU is not an isolated example in distance learning. Beyond this, Lee and Choi (2011) argued that the interrelationship among diverse dropout factors has not been systematically addressed. Muljana and Luo (2019) identified three factors influencing distance learning retention: 1) institutional factors, where findings showed that institutional stakeholders believed that the quality of student support services impacted on retention levels. 2) instructor (teacher) factors, indicated that strong pedagogical approaches such as the facilitation of student engagement, creating a sense of community, instructor engagement and course design, improved student retention. 3)
learner (student) factors identified that students’ self-regulation and self-efficacy were major factors as to whether they remained on their study pathway. These three factors are also identified as issues for this research. For example, the influence on resistance to using the EAI dashboard is in part led by the institutional structure of the OU and the changes to existing systems discussed in Chapter One Section 1.3 (such as core system changes, AL contracts, and tuition policies). There are strong beliefs among some ALs that their existing teaching approaches are sufficient to support student success without using PLA.

There is also the argument that there are advantages in that technology allows for students from across nations and countries to work collaboratively together in a global learning community (An and Kim, 2009) as the growth of technology has helped to make distance learning an attractive option (Lee and Choi, 2011). Distance learning can also appeal to specific student groups, for example, less confident students may feel more comfortable contributing to an online discussion rather than speaking up in a face-to-face course (Drab-Hudson et al., 2012). In a recent initiative, OU student support services (SST) now follow up students who do not submit their assignment and who have not requested an extension by sending an email and the opportunity to liaise with their tutor or receive additional study support to catch up. This has proved successful in encouraging students who might have had concerns about continuing their studies. However, SST intervention provided after the assignment is submitted, for some students is too late compared with using EAI indicators where tutors are alerted to passive withdrawal prior to assessment submission (Chapter Two Section 2.3.2).

The following section addresses issues arising from the initial pilot study undertaken in preparation for this research and outlines the limitations which led to the development of a more robust research design from the initial study conducted in 2018 with five (N=5) participants and how the findings led to significant changes to the main study research design.

3.3 Pilot Study

This section provides a review of the initial study, data gathered, and the limitations leading to the development and changes to the research design for the main study. The initial pilot study for this research was conducted between January and March 2018. The sample was formed of five (N=5) ALs teaching across three OU faculties FBL; STEM; WELS. Data were collected from semi-structured interviews which took place synchronously online using Adobe Connect: an online classroom environment with the

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2 These participants were not part of the main study
capacity to screen-share and record interviews. The online room was accessed via a secure link only available to participants and me. The initial study was based on a self-selected convenience sample of ALs who have used the EAI dashboard at least once but with differing experiences and with different views about its usefulness. Using a phenomenological approach allows for these experiences and attitudes to be explored in detail and for this to form a picture of their motivations.

The study findings indicated some acceptance of EAI by ALs but also a level of resistance. However, the resistance was primarily due to lack of understanding of the scope of PLA generally. There was evidence of reliance on the VLE data rather than the predictive data and consensus that the culture of the OU impacts on EAI use as the communication from management about of EAI has been limited. One theme emerging from the data which was less expected was the ethical implications of using PLA and whether the data should be used by students rather than the ALs.

3.3.1 Lessons Learnt from the Pilot Study

The set of interview questions used in the pilot study did not raise enough discussion regarding the ease of use and usefulness of EAI; participants commented on their perception and experiences of EAI, but more probing questions could explore RQ1 and link the findings to the theoretical models discussed in Chapter Two. Whilst all participants pointed to a lack of faculty support, the interview questions did not probe their perceptions of this sufficiently. One participant held the view that management should not be involved in encouraging ALs in using EAI as this could be adding pressure of workload. There is insufficient detail to draw any conclusions from this and the interview questions needed to be remodeled to allow for more discussion and further analysis.

Ethical issues relating to EAI were not sufficiently addressed to understand whether this influences the decision to use EAI. In the pilot study this was a significant concern raised, therefore interview questions were modified to address this and create a better link to the existing body of literature on ethics (Chapter Two Section 2.4) and the theoretical models (Chapter Two Section 2.5).

The fact that the focus of EAI use was predominantly focused on the VLE data was expected, but it raised questions about whether this was because participants saw this as the most important aspect of EAI or whether they did not understand the other EAI predictions. To address this limitation and by reviewing existing literature, the use of eye-tracking and screen-sharing was adopted for this thesis to give a visual picture of how ALs use EAI and a more in-depth understanding of actual use.

3.4 Participant Selection for the Main Study

Whether the methodology employed is quantitative or qualitative, sampling methods are intended to maximise efficiency and validity (Morse and Niehaus, 2009). Sampling needs
to be consistent with the aims and assumptions of either method or in the case of mixed methods research it must meet the needs of both. The interviews for the main study were conducted over the period from February 2020 to May 2020.

Participants for the main study were selected using purposeful sampling using a criterion approach. In criterion research, the researcher first identifies a criterion that is important to the research (EAI use) and then identifies the participants who have the necessary information to meet the criterion (ALs who have used EAI) (Palinkas et al., 2015). This involved identifying and selecting individuals who are especially knowledgeable about or experienced with a phenomenon of interest (Creswell and Plano Clark, 2011). Palinkas et al. (2015) stated that when starting out in the research process it is not always possible to know whether the sample will meet the research needs. Applying purposeful sampling strategy is challenging and it is necessary to take an iterative approach of sampling and re-sampling to draw an appropriate sample to ensure theoretical saturation occurs (Miles and Huberman, 1994). For this research the decision was taken to focus on ALs who had used the dashboard therefore non-users were excluded from the sample as they would not be able to participate in the observation of use (RQ3). Further, non-users would not be able to report on criteria to answer RQ2 which is based on the theoretical models discussed in Chapter Two Section 2.5. For example, it would not be possible to report on the determinants of the UTAUT model such as their experiences of effort expectancy (EE) or performance expectancy (PE) as well as the social influences (SI) of using PLA.

The sample was therefore taken from ALs who had used EAI at least once and would be able to report on their experience and demonstrate their use. Recruitment was by invitation of ALs who had attended an EAI briefing session. The initial response to this was limited with five (n=5) responses. Further recruitment was via a supportive colleague who posted on a tutor forum and from this, one (n=1) further participant was recruited. Three (n=3) more participants came forward following their participation in a different project which mentioned this research, and two (n=2) were recruited following an expression of interest having heard about the research from colleagues. While the participant sample was primarily purposeful in that it led to the required participants with correct experience taking part, there was also an element of convenience or self-selected sampling particularly for the eye-tracking element of the research as it was necessary to attend a face-to-face interview to use the eye-tracking laboratory. As ALs are based across the entire UK it was not practical for some to participate in research which meant being on campus. To this end interviews were arranged to coincide with other meetings participants were attending on campus, those who could easily travel to participate, or those who were already based on site. For the semi-structured interviews and the screen-share interviews, convenience was not an issue as these were conducted online. Invitations went to ALs across a range of faculties and the demographics of those who
took part is shown in Table 4. Figure 15 shows the breakdown of which participants took part in each study.

**Table 4. Demographic background information**

(See Table 4. Demographic information of participants.)

<table>
<thead>
<tr>
<th>Participant</th>
<th>Gender</th>
<th>Age</th>
<th>OU Teaching Experience</th>
<th>Non OU Teaching Experience</th>
<th>Teaching Qualification</th>
<th>Faculty</th>
</tr>
</thead>
<tbody>
<tr>
<td>P01</td>
<td>Female</td>
<td>35-44</td>
<td>8 years</td>
<td>None</td>
<td>None</td>
<td>STEM</td>
</tr>
<tr>
<td>P02</td>
<td>Female</td>
<td>Prefer not to say</td>
<td>21 years</td>
<td>HE and Vocational (past)</td>
<td>PGCE</td>
<td>WELS</td>
</tr>
<tr>
<td>P03</td>
<td>Female</td>
<td>45-54</td>
<td>2 years</td>
<td>Primary School (past)</td>
<td>PGCE</td>
<td>WELS</td>
</tr>
<tr>
<td>P04</td>
<td>Female</td>
<td>45-54</td>
<td>15 years</td>
<td>None</td>
<td>FHEA</td>
<td>FBL</td>
</tr>
<tr>
<td>P05</td>
<td>Male</td>
<td>45-54</td>
<td>5 years</td>
<td>None</td>
<td>FHEA</td>
<td>FBL</td>
</tr>
<tr>
<td>P06</td>
<td>Female</td>
<td>45-54</td>
<td>8 years</td>
<td>Vocational Education (past)</td>
<td>FHEA</td>
<td>WELS</td>
</tr>
<tr>
<td>P07</td>
<td>Male</td>
<td>35-44</td>
<td>11 years</td>
<td>None</td>
<td>FHEA</td>
<td>WELS</td>
</tr>
<tr>
<td>P08</td>
<td>Female</td>
<td>45-54</td>
<td>12 years</td>
<td>None</td>
<td>None</td>
<td>None</td>
</tr>
<tr>
<td>P09</td>
<td>Male</td>
<td>65-74</td>
<td>16 years</td>
<td>Other HE Institution (presently)</td>
<td>PGCE</td>
<td>WELS</td>
</tr>
<tr>
<td>P10</td>
<td>Male</td>
<td>45-54</td>
<td>3 years</td>
<td>Other HE Institution (presently)</td>
<td>PGCE</td>
<td>FASS</td>
</tr>
<tr>
<td>P11</td>
<td>Male</td>
<td>35-44</td>
<td>3 years</td>
<td>Other HE Institution (presently)</td>
<td>PGCE</td>
<td>SFHEA WELS</td>
</tr>
</tbody>
</table>

Arts & Social Sciences; (FASS) | Business and Law (FBL) | Science, Technology, Engineering & Mathematics (STEM) | Wellbeing, Education & Language Studies (WELS); | Fellow of the Higher Education Academy (FHEA) | Senior Fellow of the Higher Education Academy (SFHEA) | Post Graduate Certificate in Education (PGCE) |
3.5 Data Collection: Instruments

Fetters (2019) argued that the potential results from your choice of methods can only be evaluated in terms of the goals and purposes behind your original research question. As identified in Section 3.4.1 in the lessons learnt from the pilot study conducted in 2019 and on reflection of the methods chosen, the conclusion was that the RQs led to limited findings. To provide a deeper analysis the use of eye-tracking and RTAP/screen-share and CTAP interviews and led to the third RQ: RQ3: What are Associate Lecturers’ (a) perceptions of the use and usability of PLA and (b) actual use as measured by fine-grained eye-tracking approaches and observation of use? To complement the findings from the semi-structured interviews. Figure 16 illustrates the three studies to answer the research questions.
Figure 16. Research studies conducted

Study One: Semi-Structured interviews (discussed in Chapter Four)
Study Two: Eye-Tracking and RTAP interviews (discussed in Chapter Five)
Study Three: Screen-Share and CTAP interviews (discussed in Chapter Five)

### Study One
- 11 Semi-Structured interviews with Associate Lecturers who have used the Early Alert Indicators (EAI) dashboard. Interviews carried out using the same interview questions for each participant.
- Theoretical concepts used to inform the interviews: The Theory of Planned Behaviour; The Decomposed Theory of Planned Behaviour; Unified Theory of Acceptance and Use of Technology (UTAUT)

### Study Two
- Six Eye-Tracking interviews with Associate Lecturers who have used the EAI dashboard. Interviews carried out using a visualisation of the EAI dashboard using the same anonymised visual dashboard data set to the same week.
- Retrospective Think Aloud Protocols used to collect data

### Study Three
- Five Screen-Share interviews online with Associate Lecturers who have used the EAI dashboard using the same anonymised visual dashboard data set to the same week.
- Concurrent Think Aloud Protocols used to collect data

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Figure 16. Research studies to address the research questions.

### 3.5.1 Semi-Structured Interviews Study One

The semi-structured interview questions were sectioned so the first part of this process was to collect basic information (ensuring consent forms had been signed and information had been clearly understood). Questions were designed to be broad, unambiguous, and open-ended with scope for participants to approach their answer according to their experience. Questions also related specifically to participants experiences of both the use of the EAI dashboard and their wider experience of teaching and use of technology. They were informed by pilot findings (discussed in Section 3.4).

It was important to acknowledge that my personal experience/context might influence the research process thus my position as an AL using the EAI dashboard and my role in supporting ALs (who also use it) was acknowledged. The interviews conducted in the study used the exact same question sets but the experience of each participant was different, and how they interpreted the questions prompted different responses. For example, where some ALs used EAI regularly and felt confident in working with the data, others were less experienced and less confident in using it. Prompting questions allowed for scope to explore this further. Hefferon and Gil-Rodriguez (2011) also pointed to the importance of probing questions as these often elicit rich responses and uncover information which might otherwise be missed, and consequently probing pointers were
included to develop the questions where necessary (Appendix 2).

The semi-structured and eye-tracking interviews were conducted face-to-face on campus at Milton Keynes in the eye-tracking laboratory. Being able to introduce myself in person allowed for some time to relax and settle into the room. Whilst the topics discussed were not sensitive, there were some questions which could raise concerns as participants were asked about the level of support they received from their managers to use EAI. I was aware this could cause concern and before the interview, participants were told that they could withdraw from the interview or decline to answer any questions they were uncomfortable with. DiCicco-Bloom and Crabtree (2006) pointed to the importance of trust and a respect for participants and their shared information. Being face-to-face meant that we could go through the consent and information sheets together and clarify points which is less easy online (although not insurmountable) and was an opportunity to reinforce that they could withdraw from the interview or decline to answer specific questions at any time.

### 3.5.2 Eye-Tracking Observation Study Two

Eye-tracking has been used by psychologists and linguists to study basic cognitive processes during reading and other types of information processing (Rayner, 1978; Rayner, 1998). Eye-tracking technology determines where a user is gazing at any time and records eye movements. It uses heatmaps and gaze plots to show the focus of attention. By tracking eye movements, it is possible to see how long a participant looks at a point and how much effort they use to address a specific issue.

Research is not a linear process and changes along the way can be advantageous in leading to a more developed and richer research outcome (Baškarada and Koronios, 2018). Conklin Pellicer-Sánchez and Carrol (2018, p. 2) described eye-tracking as ‘a window into a largely unconscious behaviour.’ For this research participants were asked to carry out the eye-tracking task uninterrupted and then watch a recording to view and reflect on the process, commenting accordingly at intervals to answer questions on the actions taken using RTAP (Gu, 2014). Eye-tracking involved collection of real-time, synchronous data with the capacity to provide information about the participant’s engagement with the EAI dashboard as it happened. For this research, using eye-tracking along with RTAP provided a contrast to the self-reporting using semi-structured interviews allowing for the element of unconscious behaviour or actions to be observed. Whilst self-reports provided an understanding of the thought processes and were particularly important for ascertaining beliefs and perceptions, supplementing this with eye-tracking provided a richer and holistic approach with a synchronous investigation of actual usage. Observing eye movements indicated what participants observe but beyond this it identifies how much attention is given to specific areas. (Pellicer-Sánchez, 2020).

By using eye-tracking, it is possible to see where a participant’s gaze falls and measure their fixation: the point at which the cognitive system ‘perceives and processes’ visual
input and plans where to go next on the screen (Conklin et al., 2018, p. 1). It also allows for the identification of a much clearer gap in research and therefore had the potential for more robust outcomes, by providing for more in-depth understanding of the processes employed by ALs when using EAI. The inclusion of eye-tracking data also allowed for the collection of quantitative data to support the findings. For example, it is possible to measure and compare AOIs saccade activity (the eye movements such as twitches or jerks) and analysis of the most used and underused aspects of the dashboard allowing for numerical comparison across participant use. By using a gaze plot which indicated the fixations and saccades gave an indication of where on the dashboard participants did and did not focus their attention thus allowing for discussion with the participant to develop a deeper understanding of their rationale. If they ignored a specific part of the dashboard, was it because they already had knowledge of that area, so they did not need to look at it in any detail or was it because it was an aspect which they did not find useful or did they find it difficult to understand? In effect therefore, eye-tracking allows for the observation of unconscious actions (Conklin et al., 2018).

Using eye-tracking allows for relatively fast output of eye-tracking metrics, including visualisations, for example playback to participants can occur directly after the process thus eliminating time lapses between collecting data and viewing it, and allowing participants to reflect on their eye-tracking behaviour. As it is a synchronous process it gives a direct measure of observation rather than depending on recall alone, which may make for richer data (Cocklin et al., 2018). Importantly for this study, it provides rich quantitative data which can be used as statistical data to support qualitative data collection.

The observations in this research took place at the Jennie Lee building eye-tracking lab (which is specifically designed to conduct eye tracking research) using Tobii Studio hardware which works as a platform for the recording and analysis of eye gaze data. From this it is possible to interpret the areas of interest AOIs (discussed in Section 3.7.2). The Tobii Studio X3-120 (dark pupil tracking) eye-tracker was used to collect participants’ eye movements at a range of data points every 3.3 to 33 ms. The 130 eye-tracking component was integrated into a 23-inch flat panel display desktop monitor with a maximum resolution of 1920 × 1080 pixels. The eye movements were recorded with Tobii Studio 3 software. Analysis of the data was carried out using Tobii Studio 3.4.5 compatible software (Tobii Studio 2016).

Using eye-tracking has its drawbacks and challenges, for example, while movements provide a dynamic trace of where attention is being directed, there can be inconsistencies. This can be related to poor instruction of the task or failure to complete a calibration task successfully beforehand, leading to loss of data if it is not valid. Calibration shows a series of points on the screen, which participants need to follow, the level of calibration accuracy
is reported on the screen following completion, and if it is not successful it can be repeated (Cocklin et al., 2018). Calibration is essential as eye-tracking is a tool which is only as useful as the effort that is put into its use; therefore, its limitations need to be understood. Some reports have found that wearing glasses can affect the calibration and additional attention is needed to address this Cocklin et al. (2018). It requires the participant to sit still once the screen is calibrated which could affect both their comfort and their ability to concentrate in the way in which they would if they were performing the task without the eye-tracker (Holmqvist, Nyström and Mulvey, 2012). Holmqvist et al. (2011) argued that the validity of research results based on eye movement analysis are dependent on the quality of the eye movement data as eye data can contain noise and error which must be taken account of. In studies conducted by Conklin et al. (2018) between 10%-60% of the data collected using eye-tracking was unusable. Due to the small sample size and through participants’ willingness to persevere with the calibration process, in this research it was possible to include data from all participants.

### 3.5.3 Screen-sharing Observation Study Three

Where the initial intention for this thesis was to conduct eye-tracking observations with all 11 (N=11) participants, the pandemic and Covid-19 restrictions necessitated a move to online interviews with a synchronous screen-sharing activity. From an ethical and methodology perspective, this meant significant changes in the research design and how the interviews were conducted. Jones (2011) pointed to the requirement for ethical researchers to adapt their ethical obligations towards participants when working online, to address giving security of confidentiality and privacy as discussed below.

Deakin and Wakefield (2014) discussed advantages and drawbacks of online synchronous interviewing; it can allow for more flexibility; neither the participant or researcher need to travel, it allows for greater flexibility and reduces costs. Deakin and Wakefield (2014, p. 603) further reflected on their own online interviews and noted that ‘while potential research populations have become increasingly geographically dispersed, technological advancements and software have made communicating over large distances more feasible’. There is the risk of technical problems (such as a drop in broadband width) which can affect the rapport between participant and interviewer. There is also the possibility that participants feel less invested in the process and therefore drop out. Salmons (2012) argued that online interviewing and the subsequent separation of researcher and participant can be a practical and methodological challenge as subtleties in communication can be lost.

Because many web video conferencing tools allow for a full range of visual and verbal exchange there was scope for a synchronous interview partially resembling face-to-face communication, where both verbal and nonverbal signals can be included although they are more limited than in face-to-face interviews. Because video and audio interactions can
be easily captured using desktop software, the decision to use MS Teams was made as this platform has the function to give the participant control of the interviewer’s screen to increase confidentiality. It was necessary to share an anonymised version of the EAI dashboard to protect student data, which was of paramount importance, therefore participants needed to use my dashboard via my computer desktop rather than their own. By giving them control of my screen they were able to navigate the EAI dashboard remotely.

Another consideration due to the shift to online interviews was the collection of visual as well as audio data as these identified participants on the screen. Written and verbal reassurance was given that only myself and my supervisors (if needed) would have access to the data and that it would be destroyed once the data was analysed, and all transcribing would be done by me to avoid needing to share data with anyone else.

One advantage of online interviews is that carrying out interviews in a personal space can be advantageous for participants to feel comfortable. It also can be an impingement on privacy where visual data is being collected. Using MS Teams meant participants could use a background picture to obscure their surroundings and using my screen remotely mitigating the risk of open pages on their computer. The use of Adobe Connect was considered, however whilst Adobe Connect allows for a high level of confidentiality, previous user experience as an AL and from its use in the pilot for this study, indicated that the playback function was not clear, the webcam option is limited, and the ‘give control’ of the screen to the participant option was not available.

### 3.5.4 Retrospective and Concurrent Think Aloud Protocols

RTAP is a research method used to gather qualitative information on participants’ experiences of using a particular system and is carried out after the task (in this case eye-tracking observation of EAI use) has been completed and is stimulated by using a visual reminder (in this case video replay) (Guan et al. 2006). Through using RTAP in conjunction with eye-tracking participants were able to explain why they used the EAI dashboard in the way that they did, and what they hoped to achieve by their actions, including how they would use the information to support students. While eye-tracking shows fixation points and saccades, it does not explain why a person fixates at a given point or whether they are consciously paying attention (Conklin et al., 2018). Using RTAP gave participants the chance to review their actions and discuss their rationale.

CTAP was described by Güss (2018) as a method by which thoughts are verbalised whilst performing a task. Through using CTAP in conjunction with screen-sharing, participants were asked not to analyse their thinking, but to spontaneously verbalise what they were doing whilst carrying out the same task as those participants participating in the eye-tracking study. One issue arising from using CTAP was ensuring validity insofar as: did the task of thinking out loud influence the participant’s cognition while carrying out the
task? Ericsson and Simon (1993) argued that so long as the instruction is clear, this should not influence the outcome. This, they suggested, can be overcome by not asking specific questions but just allowing the participant to talk freely without interruption. To this end participants in this study were asked to explain their process with minimal interruption.

While both approaches have positives and negatives, in this research RTAP participants were less distracted. The RTAP interviews also added depth to questions such as: ‘Which actions did you choose? Are there areas of the dashboard you do not look at and if so, why not? Conversely, screen-sharing the EAI dashboard using CTAP, meant that thoughts were verbalised whilst performing the task and therefore the data analysis was dependent on how much information was relayed.

### 3.6 Methods of Data Analysis

This section addresses the methods of data analysis for this research. Thematic Analysis (TA) was used to analyse qualitative data from the semi-structured interviews (RQ1, RQ2). TA was described as 'a method for identifying, analysing, organising, describing and reporting themes found within a data set' (Braun and Clarke, 2006, p. 79).

Eye-tracking metrics addressing the most used areas of interest on the dashboard were used to measure experience, test usability and gather feedback on how ALs used the EAI dashboard. It also measured efficiency to provide further validation for the verbal responses given from the semi-structured interview questions, particularly as the verbal response given to the question may not always be accurate if there are misunderstandings about the EAI dashboard functions.

#### 3.6.1 Thematic Analysis

In TA, themes are developed from the codes across all data items. A theme captures important information about the data in relation to the research question and is a patterned response within the dataset (Braun and Clarke, 2006). A theme is then broken down into subthemes focusing on one element at a time. It provides a set of clear procedures to carry out in-depth analysis and gives the researcher reflexivity in how they approach data analysis (King, Horrocks and Brooks, 2019). Nowell et al. (2017) suggested that TA is a method which gives the opportunity to highlight both the similarities and differences of participants, but beyond that, it provides the possibility of uncovering unanticipated findings. It gives a description of the data but also gives an interpretation of the analysis to identify both implicit and explicit themes through the coding (King et al., 2019).

For this research the level of detail of coding helped in gathering ideas from the interviews. They were grouped together to develop the themes to most accurately answer the RQs. Coding also took account of the suggestion by Braun and Clarke (2006) that ideally, from the codes, several instances of a theme may emerge across the dataset, but
that more instances do not necessarily mean the theme itself is more crucial. King et al. (2019) suggested that so long as the single theme contributes to the analysis and is relevant to the research question, it is appropriate to include it. Disadvantages of TA are highlighted by Nowell et al. (2017) who argued that whilst it is flexible in how it is used, this can also lead to inconsistency, and the fact that there is limited guidance on how to apply it means that it is not always clear as to the importance of being rigorous, and what is actually meant by ‘rigorous’ as it is subjective. To mitigate the potential for inconsistencies, the framework for TA proposed by Braun and Clarke, (2006; 2013) was used to organise the analysis process: 1) Familiarisation with the data. 2) Generation of initial codes. 3) Search for themes. 4) Review of the themes. 5) Definition of the themes. 6) Write-up of the analysis.

**Familiarisation with the data:** All transcripts were initially read as raw data; taking the content at face value, rather than attempting to categorise and code. As suggested by King et al. (2019) too much emphasis on the RQs at this stage can detract from the experiences and perceptions of the participants. It is important to become immersed in the data without expectations and to allow the participant voice to come through. Larkin et al. (2012) pointed to the importance of questions being designed to be broad, unambiguous, and open-ended giving scope for participants to approach their answer according to their experience. One issue arising from this was how to manage data when it became disparate. For example, one participant (P02) was very experienced in the use of the EAI dashboard and was forthcoming with information, where another was precise in her answers and contributions were limited according to her scope (P04). What did emerge was that it was not necessarily the quantity of information, which was important but moreover, it was what lay within the answers which mattered. Choosing what was relevant (and what was not) was more challenging with the participants who had a lot of experience using EAI and despite the brevity of the contributions from some of the less experienced EAI users there was also some rich data particularly as to why they did not use it regularly. Because some of the transcripts were over 10,000 words, immersing myself in the data by reading the transcripts alongside viewing the video coverage led to a deeper understanding without the feeling of pressure to start the coding process.

**Generation of initial codes:** Once fully familiar with the raw data, initial coding was developed organically according to factual responses. From here, and using NVivo 12 software, main points which were helpful to understand the most relevant experiences and perceptions of the participants were highlighted to create codes. According to Creswell (2015, p.156) ’Coding is the process of analysing qualitative text data by taking them apart to see what they yield before putting the data back together in a meaningful way.’ Whilst coding is to serve a purpose, it is not the end point but rather it is a way of organising the dense data associated with qualitative research to report on the findings (Elliot, 2018). Making the decision of how many codes were needed was one of the challenges faced in
this research, particularly given the wide-ranging academic views regarding the number of codes needed. Creswell (2015) suggested coding into about 30 to 50 codes initially and ultimately reduce to the region of around 20 codes. From these codes several themes should emerge (Creswell suggested about 5-7 themes) which can then be used to form final section headings. Conversely, Saldaña (2016) cautioned that insufficient codes can overgeneralise the process, particularly because excluding codes which do not generate multiple code frequencies can mean that anomalies could be missed, as the significance of a code is not determined by its frequency.

For this research, initially 50 codes were identified and broken down into 22 parent codes and 20 child codes within NVivo 12. Where possible, the information was coded according to either the four UTAUT determinants (discussed in Chapter Two Section 2.5.3) of Effort Expectancy, Performance Expectancy, Social Influences, and Facilitating Conditions, or the Theory of Planned Behaviour determinants of Behavioural Beliefs, Normative Beliefs and Control Beliefs (discussed in Chapter Two, Section 2.5.1). Those codes which did not fit these categories were coded separately as indicators of where the existing theoretical models did not provide sufficient support for the use of PLA. Coding sources were analysed from both semi-structured interviews and RTAP and CTAP interviews. The rationale for this was that the semi-structured interviews are self-reports of AL experiences of using the EAI dashboard and the think aloud interviews provide additional nuanced data on actual use which add depth to the semi-structured interviews.

**Search for themes:** When all the data had been initially coded and collated this phase involved sorting and collating all the potentially relevant coded data extracts into themes. One issue arising was the complexity of discriminating between what was a code and what was a theme. Creswell (2015) suggested that this is a common issue for researchers and that often what starts off as a ‘code’ often becomes redefined as a ‘theme’. Saldaña (2016, p. 15) contradicted this and defined a theme as an ‘outcome of coding’ rather than an actual code. He argued that the primary level of analysis is the coding, and the secondary level is the identification of themes. Braun and Clarke (2006) suggested that codes can be merged to create a theme with more specific meaning. They also suggested that some initial codes that do not form main themes or sub-themes can be discarded.

What became apparent was that some codes did form themes particularly when addressing the ethical use of EAI data and the trustworthiness of PLA dashboards. This was a particularly ‘messy’ stage of the analysis and the most time consuming one, as several different patterns were immerging and organising the themes was complicated. Concerns also arose as to whether something was being missed, so at this point it was useful to go back to the first phase and re-read the raw data to clarify and reassure that the themes were clear and concise and best placed to answer the RQs. Running word queries on NVivo 12 software provided some reassurance of emerging themes but would
not have been sufficient on its own.

**Review of themes**: Braun and Clarke (2006) argued that themes should be clear and distinct from each other, for example, if there appears to be an overlap between themes then they should be reviewed, and a clear pattern should start to emerge. Several modifications took place before the existing themes were identified. Participants commented in depth about the function to see a student’s predicted grade, and on first analysis this appeared to be within the context of the ethical implications of grade predictions, but on further analysis this appeared to be wider than ethical use as some participants did not have access to this function but thought it would be useful if they did. It was therefore identified as an independent theme.

**Definition of themes**: Themes should be cohesive to be able to fully analyse the data. They suggest that at this stage it is necessary to re-examine what it is that is interesting about a theme and why. Braun and Clarke (2006) regarded the analysis as being the stage that tells the story of the study in a way that convinces the reader that the research is valid. This involved structuring a concise coherent and logical account of the data to make an argument in favour of the analysis taking it beyond describing the experiences of the participants to uncover hidden meanings through interpretation of their accounts. One of the complexities here was unpicking views to identify whether a theme was useful to address the research questions or whether it was interesting but not particularly relevant. Discarding less useful data was challenging at first.

### 3.6.2 Eye-Tracking Metrics

Eye-tracking studies can produce large quantities of data and subsequently it is important to choose and understand the metrics necessary to answer the research question and analyse the data. Using Tobii Studio, the term ‘metric’ is used to define the different measures that can be calculated from the recorded data (Tobii Studio, 2016). These measures can be exported in different table/file formats that can either be used to get an overview of the data and extract summary statistics, or to organise the data for processing in statistical software such as SPSS (Tobii Studio, 2016). In this research, the aim of the eye-tracking data analysis was to develop a clearer understanding of how participants used the EAI dashboard, therefore rather than developing a detailed statistical analysis, the objective was to observe behaviour to support the self-reported interview responses. In view of this, the metrics from the Tobii Studio software provided the necessary depth to analyse the data for RQ3.

While there is research to support using multiple visualisations to improve analysis results. (Blaschek et al., 2014), for this research the focus of AOIs was chosen as a method of collecting data for analysis. AOIs allow for the researcher to analyse data calculated from quantitative eye movement measures (such as fixation counts and durations). A boundary is drawn around those areas which are specific to answering the RQs and which contain
the objects of interest (in this case the visualisation of the EAI dashboard) and AOIs are used to link the eye movement measures to parts of the stimuli (Hessels et al., 2015). Gaze plot data and heat maps (Chapter Five Section 5.2.1 and 5.2.2) were a secondary data source to identify the most relevant AOIs.

The following issues were considered in the research design:

**How to choose the AOIs:** The AOI should be positioned so that it contained the objects of interest clearly within the boundary (Holmqvist et al., 2015). In this research, there was a lot of visualisations which meant that even with the small sample size there were a lot of data. There is no clear trajectory for how to choose the shape and size of the AOI (Hessels et al., 2015), therefore it is subjective but as the EAI dashboard is made up of different squares and rectangles of differing sizes, this made boundaries easy to apply.

**Size:** Smaller AOIs increase selectivity and exclude more unrelated gaze but at the risk of losing some data where larger AOIs increase may capture more data but are less selective (Tobii Studio, 2016). To manage, this several factors were used; the page was sectioned according to functions on the two pages: Firstly, on page 1: **The Overall Cohort View** VLE Activity and Tutor Group which was then sectioned into *student group, short-term predictions and long-term predictions* (Figures 17 and 18). Secondly, on page 2: **The Individual Student View** which was further sectioned into *VLE Activity, Short-term predictions and long-term predictions* (Figure 19).
Figure 17. Boundaries of each AOI

Page 1. Overall Cohort View
VLE Activity = Blue boundary
Tutor Group Boundary including Student Group = Green boundary
Short-term predictions = Yellow boundary
Long-term predictions = Red boundary
(Colour shading over the graphs indicates how the AOI is identified and generated on the Tobii Studio software)

Figure 17. Boundaries of each AOI.

Figure 18. AOIs for VLE and Tutor Group Data.
Figure 19. Breakdown of AOIs in the individual student view

Page 2 Individual Student.  
VLE Activity = Blue boundary  
Short-term predictions = Yellow boundary  
Long-term predictions = Pink boundary  
(Colour shading over the graphs indicates how the AOI is identified and generated on the Tobii Studio software)

Figure 19. AOIs for individual students.

Placement: The space between AOIs may also be a factor in calculating accurate and meaningful gaze metrics for analysis (Tobii Studio 2016). Goldberg and Helfman (2010) suggested that AOIs should only be defined for objects of interest. They also stated that space around an object should depend on three factors. Firstly, the importance of capturing every fixation on that object. For this research, what was most important was the general understanding of the EAI dashboard functions and the focus on the objects of interest within the AOI which generated the most relevant data for analysis. Secondly, the amount of white space surrounding the object. For this research, white space was omitted from the analysis as it did not contribute to the findings. Thirdly, expected disparity in fixation positions across participants. For this research there were no preconceptions about possible disparities prior to analysis.

Visits: Visits are defined as the time between the start of the first fixation on the AOI until the end of the last fixation. This includes the number of visits that occur during an interval of time, how much time participants spent in the AOI and how many fixations were counted. In this research, the mean duration of time in seconds was measured to indicate those areas which generated the most interest. There was no expectation that the process would be linear, therefore revisits were also recorded in the findings.
Limitations of using AOIs: Choosing AOIs is subjective as this has not been tested in the use of EAI before. Therefore, there is no guarantee that other researchers in the same field would replicate the findings. This makes cross-study comparisons difficult as the subjective choices while choosing AOIs can lead to research differences in the choices of the AOI shape, size, and location (Goldberg and Helfman, 2010; Holmqvist et al., 2011).

3.7 Ethical Considerations

This section moves forward to look at the ethical implications of carrying out research, it considers the importance of being an ethical researcher and places my ethical position within the context of the methodology and methods chosen for this study and the structural institutions and literature informing this ethical practice particularly as a researcher within my working organisation. This Section addresses the overall responsibilities of research to do no harm (BERA, 2018).

3.7.1 Researcher Responsibilities

The role of education research is to extend knowledge and understanding of all areas of educational activity and from all perspectives, including those of learners, educators, policymakers, and the public (BERA, 2018). Costley and Fulton (2019) described ethics as a set of moral principles to ensure the research design and the process are ethical. The inclusion of an ethical approach should therefore maximise the benefits for both participants and societies in general. Taking an ethical approach should strive to retain the rights and dignity of individuals and groups and ensure it is conducted with integrity and transparency (ESRC, 2015). It is thus incumbent on all educational researchers to openly address issues which might influence their work and to take account of issues such as remaining transparent and honest in carrying out studies and remaining committed to ensuring data is reliable, credible, valid, trustworthy, and objective (BERA, 2018).

The Economic and Social Research Council ESRC (2015) outlined five research principles: 1) Educational research should reflect the different principles of a democratic society and therefore be mindful of the inclusion of a range of values, interests and perspectives; 2) Research should respect the confidentiality, diversity and the dignity of all groups and communities; 3) The researcher should carry out their role with social responsibility; 4) Findings should be responsibly reported; 5) All research should be with the intention of maximising benefits and minimising potential harm (ESRC, 2015).

Stutchbury and Fox (2009) stressed the importance of behaving ethically as a researcher and they developed a framework for addressing ethical practice to ensure there is a defensible moral basis throughout. Using their model, consideration was given to ensuring that this research was:

1) **Worthwhile and contributed to existing research**: This research draws on the experiences of ALs using EAI and has built on the existing stream of work in the OU
(Herodotou et al., 2017; Herodotou et al., 2019; Herodotou et al., 2020) as discussed in Chapter Two. It addresses specific gaps including understanding the experiences of ALs using EAI by using in-depth discussions based on observations using eye-tracking, or screen-sharing, to identify a more elaborate understanding of ALs' behavioural intentions and attitudes to using EAI and their beliefs about its place as a tool to support teaching.

2) **That it is conducted responsibly.** Interviews were conducted following national ethical guidance as well as the Open University Human Research Ethics Committee (HREC) guidance, *(HREC reference number: 2979)* ensuring all required permissions were sought prior to data collection and updated where redesign took place. The research was carried out within the requirements of General Data Protection Regulation (GDPR) (2016). A Data Protection Impact Assessment was completed and entered onto the OU data asset register under the lawful basis for processing of legitimate interest.

Consideration was given to recognising that participants give consent based on what researchers believe will be analysed but this can change during the research process (Braun and Clarke, 2013). Due to Covid-19 restrictions there were several research design changes which needed to be acknowledged, and consequently, informed consent changed to reflect this. Six interviews took place face-to-face for which an information sheet and informed consent was signed (Appendices 3 and 4) but when this was no longer possible, the design changed to working on an online environment using an online screen-share activity rather than eye-tracking in a lab context. This led to another application to HREC and new information and informed consent forms and information forms to continue the research with five more participants (Appendices 5 and 6).

3) **That research is carried out in a respectful and sensitive manner building trust with participants and maintaining honest dialogue throughout.** My AL teaching role within the organisation is broadly the same as that of the participants in the study. Differences occur according to the modules taught (although some participants taught the same modules as me) but we were working within the same organisation (and within the same framework for practice) thus we had a shared understanding of the AL role. Having an in-depth of awareness of how EAI works brought with it the risk of assumptions (for example the belief that others would find it beneficial because I do) however the process of research is to objectively analyse the views of others and recognise that their constructs offer more insight into the bigger picture (Bevan, 2014). I have my own perspectives on the use of EAI and PLA and as such it was important to be aware of personal knowledge and the impact it may have on the research process. I therefore made every attempt to bracket these preconceptions to ensure my perspective did not influence participants in their reporting of their own experiences.

4) **That research is carried out using deontological ethical thinking** to ensure that participants were informed of the whole process and fully understood the realms of the research including their role as participants, how their data would be used and how and to
whom it will be reported: The importance of taking a deontological approach is stressed by Braun and Clarke (2013) insofar as an ethical process should not just address the outcomes of the research but should inform the whole process as research is an iterative process. The BERA Ethical Guidelines (2018) state that voluntary informed consent should be given prior to research taking place. Informed consent can also be obtained at different points throughout the study. In this case information was given to participants in advance and in writing with clear indications of expectations including commitment to anonymity and confidentiality. Participants were also given information that they could withdraw their participation and their data would be destroyed by request in line with BERA, (2018) and the OU Human Research Ethics Council (HREC) guidance. Further to this I would argue is the integrity and responsibility towards the relationship with colleagues and the respect towards the organisation within which the research is being conducted. As well as being a researcher, I am also an employee of the OU and a member of a professional body to which I am accountable for upholding professional standards. In my role I shared many of the principles of professional pedagogy with my participants, but we do not always agree about how we use and make sense of practice. My role as an advocate of using PLA can be at odds with participants’ professional pedagogical beliefs.

Prior to interview, my involvement in the EAI project was disclosed as was my AL role within the organisation. Information was given to all participants regarding the intended submission of an EdD thesis using BERA (2018) guidance on informing participants about the outcomes of research. As pointed out by Butler-Kisber (2010) there is a fundamental difference between reading about completed findings and ongoing discussion, therefore participants were encouraged to participate in open dialogue, share ideas and they received updated information as part of the research process (information about the research design changes due to Covid-19 have been shared with participants).

For research to be ethical there must be a purpose for conducting it. Costley, Elliot and (2010) pointed to specific issues arising from research in exploring the social implications of the study e.g., who does it benefit and how? The research questions are designed to explore how ALs could use EAI affectively and identify whether there was resistance to using it and why, based on the existing stream of research (Herodotou et al., 2017; Herodotou et al., 2019). By addressing the actual use of EAI several social implications can be considered: How effectively is it used, how far does it contribute to student achievement, and does it function in a way which makes it accessible to ALs? Importantly, EAI is a teaching tool to support students and they are ultimately the people who should benefit. Costley et al. (2010) also suggested the importance of addressing the financial implications of the research and whether it would bring about financial gain. By addressing the deeper understanding of the social purposes, the OU as an organisation, benefits from improved student retention which in turn would have a financial benefit.
validity is commonly used in quantitative research and is rooted in positivist perspective where a researcher identifies a problem and forms a hypothesis to be tested (Golafshani, 2003). Validity determines whether the research truly measures what it was intended to measure. The term reliability is also rooted in the positive perspective and refers to the extent to which results are repeatable using a similar methodology, remaining stable over time and accounting for any bias which might influence the findings (Noble and Smith, 2015). Truth value is associated with qualitative research and is the recognition that multiple realities exist and is concerned with ensuring that the results of research accurately represent participants’ perspectives (Noble and Smith, 2015). It is therefore incumbent on researchers to ensure that the research process is valid (accurate) and reliable (consistent) throughout the different phases of the research, from data collection through to data analysis and interpretation. Also within qualitative research is the notion of trustworthiness that the research must be transparent throughout and consistent to the extent that another researcher should be able to provide rich description. The researcher must also acknowledge their ontological and epistemological position and any potential influences they have on the research (Section 3.1.2). Although variations in the use of language exist, the overall intention is that any research should meet high standards of trustworthiness (Twining et al., 2017). Noble and Smith (2015) outline the different terminology used to evaluate whether research is credible according to whether it applies to qualitative or quantitative methods, summarised in Table 5 along with explanations of how this was achieved in this research.

Table 5. Terminology and criteria used to evaluate the credibility of research findings

<table>
<thead>
<tr>
<th>Quantitative research terminology and application to qualitative research</th>
<th>How this was met in this research</th>
<th>Alternative terminology associated with credibility of qualitative research</th>
<th>How this was met in this research</th>
</tr>
</thead>
<tbody>
<tr>
<td>Validity</td>
<td>Semi-structured interviews were a valid way to ascertain the truth value of the research in understanding personal viewpoints. Quantitative methods gave a clearer picture of the actions of participants but also their actions.</td>
<td>Truth value</td>
<td>Interview questions were redesigned following the initial study. Using probing questions was a way to reframe the questions and encourage participants to focus on their own beliefs.</td>
</tr>
<tr>
<td>Quantitative methods</td>
<td>presents participants' perspectives.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Truth value</td>
<td>Recognises that multiple realities exist; the researchers' outline personal experiences and viewpoints that may have resulted in methodological bias; clearly and accurately</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Semi-structured interviews</td>
<td>were a valid way to ascertain the truth value of the research in understanding personal viewpoints. Quantitative methods gave a clearer picture of the actions of participants but also their actions.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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Table 5. Terminology and criteria used to evaluate the credibility of research findings. Source: Noble and Smith (2015).

In addressing the validity of this research, a fundamental consideration was that whilst semi-structured interviews were a valid way to ascertain the truth value of the research in understanding personal viewpoints and experiences of participants, quantitative methods gave a clearer picture of not only the experiences of the participants but also their actions. By observing and measuring their use of EAI using statistical metrics, an additional layer of understanding was added to the research to address how participants used EAI as well as why. The introduction of quantitative methods therefore increased the reliability of the data in that it included a measure of use which would be replicable by using the same data and metrics applied.

There were also limitations which needed to be acknowledged regarding the extent to which data were valid, reliable, trustworthy and credible. For RQ1 and RQ2 how the interview questions required some redesign following the initial study discussed in Section 3.4 which increased their truth value, but despite this some questions were interpreted in a different way by some participants therefore creating some response bias. An example being that for some responses, participants reported on what they believed to be the
perceptions of ALs generally rather than their own perspective. Using probing questions was a way to reframe the questions and encourage them to focus on their own beliefs, but it was not possible to know whether their responses were influenced by their perceptions of the wider AL community. According to Lincoln and Guba (1985) the researcher can only provide research information from which, the reader will decide if the findings can be applied in a new context. As noted by Barrett and Twycross (2018) a well designed semi-structured interview should ensure data are captured in key areas while still allowing flexibility for participants to bring their own personality and perspective to the discussion. This was achieved by including prompts and probing for deeper explanations to elicit richer responses.

Transferability is considered another critical issue in qualitative research, which is addressed as generalisability in quantitative research. Regarding RQ3 and the quantitative method of using eye-tracking and the large amount of data on the dashboard, specific AOIs were identified which could be viewed differently by a different researcher who might base their choice of areas on different criteria which required some mitigation. To mitigate some potential concerns about validity and reliability and to enhance credibility and trustworthiness, triangulation was used. Triangulation is the use of multiple methods or data sources in qualitative research which helps to develop a robust understanding of the phenomena studied (Patton, 1999). Whilst triangulation is associated primarily as a qualitative research strategy to test validity through the convergence of information from different sources (Denzin, 1978), for this research the use of quantitative methods was used to triangulate with the qualitative findings to add depth of understanding. To add additional validity and credibility participant or member checking is recommended (Twining et al., 2017).

In this research participants were contacted and invited to look over transcripts for accuracy and where there was uncertainty as to meaning this was followed up for verification. Interrater reliability (the extent to which two or more observers or coders agree) was applied to address the issue of consistency. Using interrater validation allows researchers to identify potential bias before the codes are used in further analysis (Nili, Tate, and Barros, 2017). For this research, inter-rating was achieved through myself and my supervisor simultaneously analysing five (n=5) of the interview scripts through a screen-share using NVivo 12 software and a constructive discussion as to whether there was agreement of the codes’ emerging themes.
3.8 Conclusion

Research is not specifically about the end goal, but rather it is also about the journey it takes to get there. Having started from a position of phenomenology and realism, the decision to take a pragmatic approach and include quantitative methods has changed the focus of the study. However, it has taken it into an area which allows for more depth of discussion, analysis, and interpretation. Developing a more reflexive approach has helped me to embrace the research through learning new skills. From having a fixed idea of having to follow a particular approach, I developed the realisation that I could have more freedom to make choices and decisions on how I shaped my research. Using mixed methods has allowed for a more nuanced (albeit challenging) study which has resulted in a more detailed fine-grained analysis.

Having addressed the methodology and methods for the research, Chapter Four presents the data from the eleven (N=11) semi-structured interviews (Study One).
Chapter 4 Study One: Semi-Structured Interviews

4.1 Introduction

Having identified the methodology and methods this chapter now moves forward to present the data from the qualitative semi-structured interviews addressing the first two research questions (RQs).

1) How do existing teacher beliefs influence Associate Lecturers’ use of PLA?

2) How does knowledge of (a) technology and (b) data literacy relate to Associate Lecturers’ use of PLA?

Section 4.2 outlines the interview structure and the theoretical models used to underpin the research, from there, in Section 4.2.1 the coding sequence and emerging themes are outlined. Section 4.3 discusses the technology use and the data literacy experience of participants using the Early Alert Indicators (EAI) dashboard (Theme 1). Section 4.4 discusses the support available to use the EAI dashboard (Theme 2). Section 4.5 discusses the perceived barriers to using EAI (Theme 3). Theme 4 is the data explaining the perceived usefulness of EAI in Section 4.6. Section 4.7 looks at the perception of the accuracy of EAI (Theme 5). The final Section 4.8 addresses the ethical use data and using grade predictions (Theme 6). The chapter then concludes to move forward to Chapter Five presenting Study Two the quantitative data from the eye-tracking observation and Retrospective Think Aloud Protocols (RTAP) and Study Three the screen-share observation and Concurrent Think Aloud Protocols (CTAP).

4.2 Interview Structure

The semi-structured interview questions were in four main sections and the same questions were asked of all 11 participants (N=11). The demographic detail of participants is discussed in Chapter Three Section 3.5. Questions were open-ended and related specifically to participants’ experiences in both the use of the EAI dashboard and their wider experience of teaching and use of technology. The interviews conducted in the study used the exact same question sets but the experience of each participant was different, and how they interpreted the questions prompted different responses.

The first set of questions were designed to develop an understanding of the participant’s level of use of technology and data literacy. Questions were measured against the Effort Expectancy (EE) determinant of the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al., 2003) discussed in Chapter Two (Section 2.5.3). The second set of questions addresses general beliefs and attitudes towards using Predictive Learning Analytics (PLA). Questions were measured against the determinants of UTAUT and Normative Beliefs, Control Beliefs and Behavioural Beliefs of the Theory of Planned
Behaviour (TPB) model (Ajzen, 1991) (Chapter Two Section 2.5.1) with the addition of self-efficacy in the Decomposed Theory of Planned Behaviour (DTPB) model (Taylor and Todd, 1995) (Chapter Two Section 2.4.5).

The third set of questions were developed to understand the level of support participants received in using the EAI dashboard from management, briefing sessions, and social influences (for example suggestions from colleagues). These questions were addressed against the determinants of UTAUT with the addition of Normative Beliefs, Control Beliefs (TPB) and self-efficacy (DTPB).

Because semi-structured interviews focus on asking questions within a pre-planned topic framework, using the theoretical models discussed in Chapter Two Section 2.5 as a guidance for the interviews was particularly important. The interview covers a wide range of concepts within each group of questions. For example, in the interview section EAI Use, beliefs and attitudes about using predictive data linked to the participants’ PE (e.g., I find the dashboard easy/difficult to use) and EE (e.g., checking the dashboard is straightforward/difficult) as well as their beliefs about using PLA. Having the framework in place helped to increase validity and reliability as well as ensuring that when coding the data, no salient points were missed.

### 4.2.1 Coding Sequences

Having outlined the responses of participants in relation to the semi-structured interviews, responses were coded and classified according to the following determinants from each model3 (Table 6).

**Table 6. Code classifications according to theoretical models**

<table>
<thead>
<tr>
<th>Theoretical Model</th>
<th>Dimensions of the Model</th>
<th>Code</th>
<th>Frequency of Code (including multiple occurrences in the same transcript)</th>
<th>Themes</th>
</tr>
</thead>
<tbody>
<tr>
<td>UTAUT</td>
<td>Effort Expectancy</td>
<td>Confidence in using EAI</td>
<td>9</td>
<td>1. Technology use and data literacy</td>
</tr>
<tr>
<td></td>
<td>Effort Expectancy</td>
<td>Knowledge of technology generally</td>
<td>21</td>
<td>1. Technology use and data literacy</td>
</tr>
<tr>
<td></td>
<td>Effort Expectancy</td>
<td>Ease of use of EAI</td>
<td>21</td>
<td>1. Technology use and data literacy</td>
</tr>
<tr>
<td></td>
<td>Effort Expectancy</td>
<td>Frequency of use of EAI</td>
<td>11</td>
<td>1. Technology use and data literacy</td>
</tr>
</tbody>
</table>

3 Repeat determinants have not been included
<table>
<thead>
<tr>
<th>Social Influences</th>
<th>Peer support</th>
<th>4</th>
<th>2. Support available to use EAI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Facilitating Conditions/ organisational structure</td>
<td>Training in using EAI</td>
<td>13</td>
<td>2. Support available to use EAI</td>
</tr>
<tr>
<td>Facilitating Conditions</td>
<td>Management support</td>
<td>25</td>
<td>2. Support available to use EAI</td>
</tr>
<tr>
<td>Facilitating Conditions</td>
<td>Peer support</td>
<td>8</td>
<td>2. Support available to use EAI</td>
</tr>
<tr>
<td>Facilitating Conditions</td>
<td>Motivation by organisation to use EAI</td>
<td>12</td>
<td>2. Support available to use EAI</td>
</tr>
<tr>
<td>Performance Expectancy</td>
<td>Usefulness of EAI</td>
<td>27</td>
<td>4. Perceptions of usefulness of EAI</td>
</tr>
<tr>
<td>Performance Expectancy</td>
<td>Attitudes to accuracy of data</td>
<td>11</td>
<td>5. Accuracy</td>
</tr>
</tbody>
</table>

**Table 6. Code classifications according to theoretical models.**

From the coding, the following themes were identified using the framework of Braun and Clarke (2006) and from here the analysis of the interviews are sub-headed to address each theme.

1. a) Technology use and b) Data literacy
2. Support available to use EAI
3. Barriers to effective use of EAI
4. Perceptions of EAI usefulness
5. Perceptions of EAI accuracy
6. Ethical use of data

The first four themes were explained within the context of the theoretical models. What also emerged were differences in how participants viewed the ethical use of student data and concerns regarding the accuracy of the dashboard when relying on algorithms. Participants had very specific beliefs about ethical concerns particularly having a grade prediction indicator on the EAI dashboard and how this might influence how Associate Lecturers (ALs) mark students' work.

4.3 Technology Use and Data Literacy (Theme 1)

The following section addresses participants' experiences of using technology and Section 4.3.1 looks specifically at participants' reports of their data literacy.

4.3.1 Technology Use

Because use of technology forms a substantial part of the AL role, five (n=5) participants described their technology confidence as being above average and used technology in everyday life. P01 reported that her skills in using EAI were good:

‘I’m very confident in the use of technology. If I don’t know something, I’ll throw myself in and have a go until I do know it, and that’s what I have done with EAI.’

(P01).

P07 described himself as confident with technology and easily able to problem solve and interpret technologies that he was unsure about. He described a high level of confidence in the use of spreadsheets, word processing, and reading and interpreting graphs:

‘I don’t know whether it’s because I am a bit of a perfectionist, but I always throw myself into working things out. So, when the EAI dashboard was first available I spent quite a bit of time going through it all, and that’s something I would tend to do for all technologies: If I need to use it, I want to be sure I understand it fully.’

(P07).

P08 described herself as confident in all areas of technology use required for her role:

‘Technology is something I try to embrace and as an AL need to use it regularly. Sometimes keeping up with changes is frustrating but it’s part and parcel of the job.’

(P08).

P10 described himself as confident in the use of technology and used innovative methods of feedback to students including audio feedback and screenshots. Having a background in working in technology:

‘I’m really interested in finding innovative ways to support students using technology and particularly in how I give feedback. I use video feedback for students so that they can hear and see what I am reporting back on, and I am always looking for new ways to use technology to support students.’

(P10).

P02 felt that there was a lack of training for ALs to use technology and that development of these skills was based on the goodwill of ALs using personal time to learn and that with more support and paid training her skills would be higher:
‘I’ve learnt myself, really. I’ve done development courses because I’ve seen the need for technology to change and I wanted to be digitalised.’ (P02).

P04 similarly also reported a reasonable level of confidence in technology but noted frustration at the number of different IT systems ALs are expected to use which are bureaucratic and slow thus time is spent learning how to use specific technologies to the detriment of developing skills in other areas:

‘My technology knowledge is good, but I am a frustrated user because I often find the systems slow or bureaucratic. I’m quite happy to use technology, I just find there’s lots of different systems we’re expected to pull on as tutors and that can be frustrating, particularly if they’re slow or not working.’ (P04).

P03 reported that she was confident in using web-based conferencing tools such as Skype and Zoom as these were integral to her role outside of the Open University (OU).

‘I’m not frightened of it. I just face it and get on with it and I normally, over time, work out what my problems are and how to solve them.’ (P03).

P09 described himself as reasonably familiar with word and Adobe Connect but not an expert in using technology other than that which is required for the AL role:

‘Technology is just a part of life now, I don’t love it, but I don’t hate it either. Working at the OU it’s important to use different technologies so it’s a case of just getting on with it really.’ (P09).

4.3.2 Data Literacy

Data literacy was also an area that most participants felt reasonably comfortable with and again reflected their skills as distance learning teachers, for example, one (n=1) participant (P01) described how working in STEM subjects demanded that she was data literate. As well as using technology in her AL role, she also felt confident in using word processing spreadsheets and databases as well as feeling confident in interpreting information such as graphs and charts.

‘I’m very comfortable with interpreting data. And maybe that is because I am a maths tutor so it would be expected of me. I can understand why not everyone would feel the same but for me it is part of my everyday work life’. (P01).

P03 reported that more complex graphs were out of her comfort zone, but she would always be able fathom them out in time. She reported being comfortable with spreadsheets and word processing.

‘I don’t like to give up on something and so have a look at it and try and find some way to fathom it out. But graphs…. it’s not my natural comfort zone.’ (P03).

P10 was confident with spreadsheets, databases, word processing, and interpreting graphs.

‘I don’t feel challenged by data, sometimes it’s just a case of spending time and working through it but I don’t mind doing that. It’s like problem solving really, it’s part of everyday life so I just embrace it.’ (P10).
P02 stated that she did not use spreadsheets but was very confident with word processing having spent a lot of personal unpaid time upskilling. Her concern was that there were assumptions that everyone was data literate and that having a skill in one area did not mean that all data could be easily understood:

‘I hate it when staff tutors send things on spreadsheets because they assume that we can use them, and we’ve never been given any training by the OU on spreadsheets at all.’(P02).

4.4 Support Available to Use EAI (Theme 2)

Section 4.4.1 addresses the support available from managers and this is followed by reports of peer support in Section 4.4.2.

4.4.1 Management Support

One of the most consistent findings from the interviews was that all participants (N=11) reported that they did not have ongoing support from their school faculties or module teams to use EAI whilst for some there was initial support, but not ongoing. Nine (n=9) participants reported that they first began to use EAI under the direction of their faculty or module team, but that the momentum of support did not continue. Some of the reasons suggested for this were given as managers stating that because encouraging the use of Predictive Learning Analytics (PLA) is only a very small aspect of their role, and because EAI is voluntary, it is difficult for managers to sustain its continued support given their other management responsibilities and particularly as using EAI is not a mandatory requirement. Three (n=3) participants noted this as an issue. Of these participants one (n=1) felt that the way in which ALs were encouraged to use EAI was autocratic in that she felt she was told she must use it. Despite initially seeing it as useful, for this participant motivational intention was affected by this approach and she now only uses it occasionally:

‘We were told to use it and the message was very autocratic i.e. “You will use it and you will go on the training and there’s no payment” and that immediately caused me a headache…… because you can imagine, different faculties are using this in different ways and as an AL I felt that I quite liked this kind of this, I think it’s a good support for tutors but I don’t think it should be perceived as ‘you will have to use it.’’(P04).

Similarly, P02 had some concerns about the way in which management introduced EAI and felt that they had taken a directive approach which was not standardised across the OU:

‘The way they’ve influenced it’s been the wrong way because for (one module) it was written into job descriptions as mandatory and of course that immediately got everybody’s back up. So, they have influenced it but not actually in the right policy framework. They’ve actually put a barrier there because people are immediately saying, hang on a minute. You know, why is this mandatory now? We haven’t had
any training. Well, we have training but it's optional and their argument from a management perspective is well, we provided the training what's wrong with the ALs? So, but I come back to this key point that they don't get that this isn't about teaching and supporting in an AL's mind. It's additional admin work.’ (P02).

Ways in which initial support was offered also varied. One (n=1) participant was offered a 2-page instruction set with links to the available training and briefing options but did not receive more information about how to access and use EAI effectively. He acknowledged that whilst this approach to providing support was limited, it was possibly explained by the fact that the module he taught was new, so demands on management time left little scope for addressing other concerns. Therefore, using EAI was not seen as a priority for managers on his module, but the consequence of this was that it did not encourage ALs to use it:

‘I think because it’s a new module that our focus is on getting it up and running. so, I don't want to be critical of the faculty in that regard. If this was an established module and that was the level of guidance I got, then I would be disappointed with it. Our, the whole module team and the AL community on that module is focused on, let's get this first one through the door. Let's make sure we can iron out the anomalies. It’s less of a priority to push the predictive analytics side of things. (P05).

Another issue raised was the lack of standardisation in how different module teams viewed the usefulness of EAI and how they therefore supported its use:

‘I know it’s hard for managers to show interest in all aspects of the teaching process and its down to us as ALs to work out our own strategies, but I have had mixed responses to using EAI. On (one module) they encourage it but (on another) it’s ignored. On (another) module, it was openly said on the forums that the module team didn't think it was helpful in any way whatsoever.’ (P01).

For another participant (n=1) there was a feeling that more could have been done to promote it as a useful support tool:

‘I do feel I've been a bit left to my own devices […..} I think because the module I first used it on was in a pilot, it was very much like there's a thing here you can use it or not use it, give it a go. But when I started so I shared how I used it with some of the module team and my staff tutor and things and it was a bit like, that's nice. I almost feel that we could have done more with it. They didn't take that opportunity and I think that's because maybe they didn't have the enthusiasm about it that I got through using it if that makes sense.’ (P11).

One (n=1) participant identified that he was the one to mention EAI to one of his module managers having found out about it from a colleague. They were supportive of the idea of using it but did not take an active role in developing this support. On another module he suggested its use on the tutor forum, but a decision was taken not to enable the full dashboard:
One (n=1) participant commented on the support that managers were given to encourage the use of EAI. She identified that she was not specifically asked by management to use EAI, and that she found it by looking around the website when she first joined the OU and worked it out for herself. As a relatively new member of staff, she wondered if she had missed out on training opportunities which were no longer available so contacted her module manager who was not aware of EAI:

‘I was never asked by anyone to use it, I found it by just exploring the website I was asked my new manager about the training sessions, but he didn’t know about them either, so I carried on trying to work it out myself.’ (P03).

Another aspect of this was whether participants attended a briefing session to develop the skills to use EAI. Four (n=4) participants attended briefing sessions primarily because they were asked to do so by managers but again there does not appear to be consistency in the expectations to do this. One of the issues raised here by three (n=3) participants was that no funding was available to attend briefing sessions and the contract basis of AL work means that attending training which falls outside of staff development is often seen as being based on goodwill therefore without financial recognition some ALs are reluctant to attend:

‘There are so many changes happening I think it’s hard for management to keep up with the next thing and the next thing, but they haven’t encouraged training by not paying ALs to do it. They depend on us doing it on goodwill and by doing that I don’t think they value it as a tool at all.’ (P02).

This response was not restricted to this question and the issue of payment to attend training was raised in several situations during the interviews. For those participants who attended a briefing session it was seen as influential on their intention to use EAI.

‘I was asked by my manager to attend a briefing when I was part of a pilot study, so I did, I was curious about this new tool, and I have to say that this was a motivation for me to use it.’ (P06).

4.4.2 Peer Support

Whilst the ongoing management involvement was rather mixed there was evidence of participants gaining peer support, with three (n=3) participants stating that they have either had support from peer colleagues in using EAI or have been instrumental in sharing their EAI skills with other colleagues and/or managers. This was a more significant
influence on their ongoing intention to use EAI as it was a more collegial and ongoing approach. There was also a sense by which peer support was a way of maintaining a support system from those ALs who shared an interest in its use. One (n=1) participant did not consider it as the role of the module managers to support her in using EAI because she had the autonomy and the skills to make the decision whether to use it or not. For her it was more useful to discuss it with peers so if she found any anomalies in the data, she would speak to colleagues to gain their perspective on how to interpret the data:

‘I think I since the initial request from management to use it I was probably more influenced by colleagues who used it rather than the module or faculty leads because it’s colleagues who are using it and they have a better understanding of what we should expect from using it too.’ (P06).

Another participant (n=1) identified that he was unaware of EAI until recently following a staff meeting where an AL did a short demonstration of its functions. He has not had encouragement from management but acknowledges that his module chair is passively supportive. His support and motivation to use it is based on peer support having identified other users and discussing the data with them:

‘To be honest I have not thought of asking for help from anyone other than colleagues as they are the ones who use it on a week-by-week basis. I don’t think I would expect my module lead to be able to help with this sort of thing.’ (P07).

One (n=1) participant found out about EAI through a project he was involved in and has not had any managerial support. He did not see this as a barrier to using it as he has technology experience, feels confident in using it and shares his experiences with other ALs:

‘I use it pretty frequently now and I have had other ALs ask me about it, so I think I know enough to be able to support them to use it too, but it doesn’t seem to be consistent as there are still a lot of people who don’t seem to know about it.’ (P10).

In terms of the role of management, although the support offered was limited this was not necessarily viewed as negative. Responses from three (n=3) participants indicated that they did not see management support as influential and nor was it necessary as they were willing to use their own volition irrespective of management, or peer support. In part, this perspective can be explained by the autonomous role ALs hold within the OU structure and the fact that therefore decisions about whether to use EAI should be in the hands of ALs and not as a directive from managers. Whilst it was evident that managerial support was not a determinant in ALs’ intentions to use EAI, attitudes toward this were mixed and as expected, peer support appeared to be a more influential determinant in intention to use EAI.

Acting on one’s own volition was also considered important and indicated strong self-
efficacy (Bandura, 1982) as identified in DTPB (Taylor and Todd, 1995). The approval of others (peers, management) is key to performing a given behaviour and that the strength of these beliefs is multiplied by the person’s motivation to comply with the beliefs of others. This suggests that despite expectations that management support does influence intention to use EAI this is not necessarily the case and peer support influenced intention to use more positively when considering the long-term use of EAI rather than management support which was a much more ‘start up’ short-term approach.

4.5 Barriers to Effective Use of EAI (Theme 3)

In terms of usage there was evidence that participants tended to either use EAI regularly or systematically. Four (n=4) participants used it weekly, one (n=1) used it fortnightly, two (n=2) used it three weekly, two (n=2) used it monthly, and two (n=2) had used it in the past but no longer used it or they used it infrequently (Figure 20). Importantly here, is the potential for bias which must be acknowledged, as the research depended on a minimum level of user knowledge of the dashboard. Where it was expected that participants would see barriers in terms of using the dashboard or lack of usefulness, the actual barriers reported were not having the time to use it, lack of training opportunities, or not having full access to all the EAI data. Therefore, time constraints, lack of training opportunities and management decisions to restrict data (in some cases) were all influential barriers to the use of EAI.

Figure 20. Frequency of occurrence of accessing the EAI dashboard

![Frequency of accessing EAI data amongst 11 participants](image)

**Figure 20. Frequency of access to EAI among 11 participants.**

Regular and systematic users: One (n=1) participant identified that she did not see any barriers to using EAI as it forms a substantial part of her teaching role. She also stated
that she would now struggle not to use it as it has become an integral part of her teaching strategy to improve student outcomes. As a regular user, she stated that what were once barriers (such as understanding the data and knowing how to act on it) are now within her control through her experience of using EAI:

> It’s reassuring, it makes me feel like I have got an understanding of what my students are doing. I think that when you remotely work, it can be quite isolating, you can start to doubt yourself. I get so few people coming to tutorials, they don’t answer my phone calls, they would rather text me on WhatsApp and I feel like I’m losing contact with my students [...]. Sometimes I will look at the other data on their demographics but generally I look at whether they’ve been online because otherwise that’s the only kind of contact I have with them.’ (P01).

For another participant (n=1) one of the biggest barriers faced is the expectations on ALs in terms of workload. Although she is keen to use it herself, she feels that others may not invest the time in it as it becomes ‘another job to do’ amongst a growing list of expectations. The balance between its usefulness and the time spent using it was an issue:

> ‘As an AL I’m told I’ve got that one little thing on (EAI) analytics to do, but I’ve also got this one little thing on mentoring, and I’ve got this one little thing on Adobe Connect from somebody else and I’ve got this one little thing... and before I know I where I am, I could spend a week doing the one little things. And it’s all on goodwill. And what are ALs? Time poor. (P02).

Another participant (n=1) identified that although he uses EAI systematically, he believed that the main barrier for most ALs is that it does not form part of the staff development process in the OU and that lack of recognition for ongoing training is a potential barrier to wider use. He also believes that the OU as an institution does not invest in its use. He stated that this is not specifically a criticism of the OU as he recognises that priorities change, but the reliance on asking people to use systems voluntarily, and the lack of investment in EAI was a concern. He also stated that if the OU recognised its value for the student experience, then it should embed EAI training into staff training and pay ALs to participate:

> It has literally been the lack of acknowledgement that this is something that does need some time invested in understanding how it works. And we’re not paid to invest that time to understand how it works, you know. And it always comes back to this conversation of ALs have two staff development days a year they’re meant to attend. But, if I added up all the things that I was told to fit into my two staff development days, they’d be very long days. (P11).

This participant also identified that he believes that teachers are sceptical of how machine-based algorithms can predict student learning needs in the way that existing teaching skills already do. He believes that by getting ALs ‘over the hump’ of trusting algorithms they would find it invaluable for how they support students:
‘I think the biggest barrier to its wider use is the scepticism of teachers when it comes to trusting algorithms. If we can get ALs over that hump I think it would break down a barrier’ (P11).

**Less frequent users:** One (n=1) participant identified that her lack of knowledge on how to use the dashboard is her main barrier. Her perception of EAI is that it is mathematically driven where her interest is more about the psychology of students and looking at patterns of behaviour therefore, whilst she considers herself IT literate it takes her longer to interpret the data and that it can be overwhelming. Despite this she does use it, but feels that she does not understand the data sufficiently to use it to its full potential which is in part down to lack of training opportunities:

‘The first thing I thought was, my goodness what a lot of analysis about students and I know you can do extreme analysis of things and I did think gosh someone's put a lot of effort into that, are people going to use it? Is it worthwhile? That's what I thought. So, I had a look to see what was worthwhile I thought it was, but I knew I had to find out more to be able to use it properly and I’m not sure that I get the best from it.’ (P03).

Another participant (n=1) identified that she did not use EAI anymore, she only used it when directed to do so by her faculty manager but feels it does not offer her anything to support students that she does not already know through her traditional teaching skills particularly as she has been an AL for over 15 years and has trust in her skills. The way in which it was introduced to her was also a barrier:

‘It links to my point about how it was rolled out. I think it was useful, but I don’t think telling tutors that they have to use it is helpful and I’m not sure that it tells me anything I wouldn’t already know as I have good communication with my students.’ (P04).

Part of the reason for this was that she only sees a part of the dashboard and because the data is limited it is not as useful as it could be:

‘I’m not sure why our faculty has taken the decision to limit the data we can see on the dashboard, but I think it makes people less inclined to use it. It’s definitely a barrier and there is nothing we can do about it. That’s what they have decided so that’s what we have.’ (P04).

P05 identified that the main barrier to using EAI was time constraints and the fact that he teaches on a new module therefore there is insufficient historical data for the predictions to be accurate which was beyond his control. He predicts that the data will be more accurate next year and therefore more useful, so he is more likely to use it more frequently.

‘Because there is no historical data of how students performed in the previous year, there isn’t anything to measure it against and I think this would put people off using it, but next year when the module has run for a year it should make it much more accurate.’ (P05).

One (n=1) participant identified that the biggest barrier to using EAI was his lack of awareness of the functions. He could see that it was a useful tool to support teaching, but
the time needed to upskill and gain the necessary training was an issue and he felt that
the time spent upskilling himself might prevent him from using it more systematically.

‘I am quite fascinated by using it but I have a lot to learn yet and that is going to be
something I need to invest in but yes I can certainly develop the skills to use it so I
don’t see it as a barrier, it’s more of a learning curve.’ (P09).

There was a range of conflicting opinions regarding barriers. Where some participants saw
using EAI as saving time, others saw it as time consuming. The common theme here was
that people who used it frequently were more likely to see it as time saving than those who
used it less frequently. Therefore, the level of motivation to use EAI plus level of experience
was an indicator of strong intention. From this there is evidence to support the expectation
that EAI as a system needs to be embedded into the wider structure of the OU and that
training and long-term ongoing investment are therefore determinants in ALs’ intentions to
use EAI. Presently, the responsibility lies with those who choose to use it on a voluntary
basis and limits the systematic adoption.

4.6 Perceptions EAI Usefulness (Theme 4)

There were different responses to the perceived usefulness of how EAI could support
students. Three participants (n=3) (P01, P08, P11) specifically stated that they saw
benefits in encouraging students across all abilities not just those at risk of non-
submission. Of these, one (n=1) participant (P01) identified that because she uses EAI
regularly, she usually knows what she is expecting to see so she looks at it as
reassurance, however she has had incidents where a student appears to be doing well
but EAI data flags up that the student is at risk part way through the module:

‘I have had examples of students doing really well and yet when I check the data it
shows me that there is a problem. For me this is important. We never know what is
happening in students’ lives, and If I didn’t see this, I would think they were doing
OK, and I might not contact them. This is when EAI is really powerful.’ (P01).

If she sees that a student has not been on the VLE she will email them to check progress
and phone the student to work on a catch-up plan and an extension if needed. Support
can be offered in a timelier manner because the information is available before it becomes
too late to catch up. She encourages students who are working to a high level to maintain
their grades hence for this participant using EAI is not only about supporting students who
are at risk of failing but also to improve outcomes for students at all levels. Another
participant also uses the student information to ensure that, as well as identifying students
at risk of failing, she can also use it to keep up the momentum of students in her tutor
group who are doing well.

‘It’s not just about students who are not going to submit, it’s also a tool for
encouraging students to do better even when they are doing well. If I can see that
someone has not done as much activity as they usually, do it is a trigger for me to
at least keep an eye out for them or if necessary, it can be a conversation opener to see if everything is ok.’ (P08).

One (n=1) participant identified that he tends to use EAI quite intensively at the beginning of the module to make sure all students are engaging. One of his modules has a strategy to phone students at the beginning of the module which some students decline. If he cannot contact them, he can check their progress on EAI and if they are engaging, he does not worry about them whereas without EAI he would probably spend more time trying to contact them:

As a student myself I tend to not depend on tutor support and I understand that that is the case for a lot of students, so if I look at the EAI dashboard data quite early on and I can see they are engaged I know that they are OK, and they might not want to speak with me which is fine. But if I couldn’t see they were OK I might try to contact them, for some students particularly at level three they just want to get on with it and tutor’s calling them all the time is just an annoyance. (P11).

A common theme was being able to identify students for whom it would otherwise be difficult to know that they had fallen behind and this was a strategy held by all 11 (N=11) participants. P02 stated that she also uses it to open conversations with students about their progress if the Virtual Learning Environment (VLE) data suggests they are not actively engaging with the module. Conversely, she acknowledged that the data can sometimes be wrong, so it is important to be aware of that when speaking to students, so the conversation needs to be sensitive.

‘I do use the data to open a conversation with students who I think are at risk but I’m very careful how I approach this. I know that the data is not always 100% accurate and I have to think about this before I strike up a conversation. I keep this in mind so as not to come across as being alarmist when I speak to them.

Sometimes they will tell you that they are OK and keeping up, but the data tells you something different. Then you have to trust your instinct and also trust the student. I can at least leave the door open for them to approach me if they want to.’ (P02).

One (n=1) participant stated that if EAI identifies that a student appears to be struggling, he could now change the way in which he words his emails according to his findings on EAI and this is something he is considering in the future.

‘By the end of November, it (EAI) was beginning to give me a bit more guidance because there was a lot more richness to it. I sent out my Christmas message to everyone. What I could have done is maybe tailored it with a slightly stronger message to some people telling them they need to focus on the two week break to catch up. And to other people, great you’ve done all your work, go and enjoy your two week break.’ (P05).

As expected, performance expectancy does have a positive effect on behavioural
intention in supporting students. Where there was an expectation that the focus of support would be toward students at risk, there was also intention to use EAI to improve the outcomes for students who were achieving good grades. Experience of technology and teaching are also influencing factors and EAI is effective in student support. When addressed in relation to the findings for RQ1 it should be acknowledged that whilst performance expectancy/perceived usefulness is positive, it needs to be seen in the light of other factors such as the barriers to use (Theme 3).

4.7 Perceptions of EAI Accuracy (Theme 5)

It was accepted by all participants (N=11) that the data for EAI was not always accurate, the extent to which these affected perceptions of usefulness and ease of use varied. One participant (n=1) noted inaccuracies in the data due to fluid data inputted into the system but that he was aware of this and was still able to interpret the data. He also had good levels of technology literacy but might not be the case for others. He also identified that not having full access to the prediction data on one of his professional modules was frustrating, so it was not as useful.

'We had this thing on one of the professional modules which is now coming to an end, where we get them to submit a formative assignment but give it a mark of 1. So, the whole system was 1, 1, 1, 1 all the way down. And, I'm thinking well that's just going, the data's going to be completely wrong after that, isn't it? So, I've had mixed use of it on other modules.' (P07).

Another indicator of the perception of accuracy was student behaviour. Three (n=3) participants expressed how student behaviour can impact on the accuracy. Another participant (n=1) identified that she found the data mostly accurate, especially as the VLE click data will identify if a student has engaged and is a quick and accurate way to identify if a student is engaging online. She acknowledged that sometimes the data does not appear accurate for reasons beyond the scope of PLA (such as students downloading materials or using different formats such as voice recorded materials). Using EAI in conjunction with other teaching strategies increases the efficacy. She described it as being a part of a jigsaw rather than the complete picture and felt confident in being able to interpret the data which becomes easier with experience.

'I think it comes with experience. I used to panic when I saw a student was not engaged but now, I tend to look at the wider picture, maybe they are away and working offline or perhaps they have studied this topic before, so they don't need to spend as much time on it. This is where I would contact the student and check. If they said they were OK with it and didn't have any worries, I would take that at face value but encourage them to contact me if they had concerns.' (P08).

Another issue raised was that students might not always use the VLE and therefore their actions might not be reflected on the EAI data:
‘You have to take into account that just because they have not clicked as many times as the other students, there is no certainty that they’re not learning but it’s another way of looking at how it helps and just kind of gives you an insight into the student. Some students work that way… they cram close to the deadline and if it works for them then you have to be respectful of their learning decisions.’ (P10). It was recognised that the data is as accurate as it needs to be but is not perfect as it cannot legislate for student choices:

‘We’ve got students who work from printed materials because they can’t cope with study on a VLE. You know, obviously, these predictions are heavily based on use of the VLE. So, if that student’s not clicking on anything, that might make me question whether that prediction’s useful for that particular student. It wouldn’t stop me using the predictions for the students overall, but it does kind of give a bit more nuance as to whether it’s relevant for the student I’m worried about.’ (P11).

Whilst effort expectancy does hold some influence on behavioural intention in the use of EAI, participants were more accepting of inaccuracies particularly if they used the dashboard regularly. Also, the more experienced a person is in using EAI, the more evidence there is that they will be able to make good use of the data.

4.8 Ethical Use of Data (Theme 6)

Most participants felt that in the correct hands, using student data was necessary to be able to give a higher level of support, but what was more of a concern was the position of students as stakeholders in the use of EAI. It was suggested by some participants that students were unlikely to fully understand exactly how their data was being used and questions were raised as to whether students knew that ALs used EAI to monitor their progress. The interview responses showed that not all participants saw the term ethics or ethical use in the same way. Where some participants were concerned about the level of disclosure that we shared with students about using EAI, others were concerned as to whether the right information was being used to create the algorithms to make the data accurate. The issue of grade predictions raised concerns for some participants as to whether they might influence ALs in how they mark students work.

Three participants (n=3) who either are, or have been, OU students, stated that they would expect that their data was being used in a way in which improved their educational outcomes. One (n=1) participant stated that we have an ethical responsibility to support students and as someone who has had positive outcomes from using EAI it is necessary and acceptable.

‘As a student some years ago, I thought that somebody was doing that sort of check anyway and when I found out that they weren’t, I was a little bit disappointed because that made me feel like it was just any other correspondence course. I thought that doing an OU degree would mean that somebody was there to support me, […] keeping an eye on whether I was doing well or not so I think it’s a good thing that we are doing that now.’ (P01).

One (n=1) participant stated that he sees the ethical position as standard practice in all
areas of education and the problem only arises if it is misused.

‘We’re offering academic support. Whether that’s as an AL or whether that’s as a university as a whole. We’re not even scratching the surface of what we could be doing. If we had servers the size of Google, we could be tracking all sorts of things and flogging all sorts of advertising to people. That for me would be unethical if we were then using that data to try and sell them something.’ (P05).

One (n=1) participant stated that we needed to remember that all the information collected from the algorithms were part of the wider OU systems anyway and therefore EAI was essentially consolidating information of what was already held. For this participant the issue was therefore less about EAI and more about the OU generally and whether data is in the hands of people who use it ethically. He saw no reason why it should not be in the hands of ALs as they were the people who were closest to the students on a day by day basis and could act upon it. He also had concerns as to whether students fully understood the extent to which their data was being used:

‘I think the point about having the software available then it probably does raise ethical and professional duties and responsibilities to use it effectively to try to support the students as well as possible and encourage them through the module.’ (P10).

Two (n=2) participants stated that for them the ethical issue was how ALs approach students and whether they do it in a supportive way rather than being combative about it. Using data was seen as a positive so long as it was used to give support rather than as a punitive measure for students who are struggling.

‘I think there are some ethical challenges with this idea of giving students TMA predictions or completion predictions if staff end up using that in a deterministic way. So, like I say, I’ll look at the chance of not completing sometimes to see if it’s got worse or better and do I need to do anything to intervene. What I absolutely wouldn’t do is say, well that student has got no chance on completing so I’m not going to waste my time with them.’ (P11).

Another participant identified that she had concerns about how we use data, but beyond that how we measure whether a student is successful and whether this should be self-defined by the student rather than teachers deciding what is success and what is not:

‘I know where I’ve got students that are struggling, I feel it’s almost intrusive to suggest this student’s not going to pass because I feel that it can limit that student’s potential and it’s a predetermined route that student is on and, what is success for our students? Sometimes just submitting an assignment, even if they’re not going to achieve a pass rate is a success. I’ve felt sometimes that, as a student, if I knew that my name was on a dashboard somewhere with a predicted outcome, how I would feel about that?’ (P04).

An area of concern was the extent to which students were aware of the data stored and used to produce PLA data and whether they ticked boxes they did not fully understand. Five (n=5) participants were concerned as to whether students explicitly agree to the use
of their data for EAI. One (n=1) participant stated that she was unsure what level of information students get about the use of data when they sign up to a module and whether they can tick a box without reading the policy.

‘Yeah. Well, I'm not quite sure. Like I said, it's great evidence, but whether they're aware that it's there as evidence that they're not logging on. I think they agreed to it, but I don't think it's explicit consent. I think its implicit consent and I have issues with that.’ (P02).

Another was also unsure how to broach students and tell them that he can see their activity online.

‘I suppose ethical issues would be around how much we tell the students, wouldn't it? I mean, are they aware that their clicks are monitored? Is it something that they agreed to at some point when they start their OU career? Do they tick a box somewhere saying, my activity on the module will be monitored? Do they know that's happening? Because if they don't, I think that's potentially a problem. I feel a little bit awkward about approaching a student and saying look, I can see you clicked a lot in week 2 but not much in week 3. It does sound a bit Big Brotherish, doesn't it? But then if I don't mention that, of course, then I'm holding on to information about them, that they don't know I know. So, that is a bit of a concern.’ (P07).

Conversely, another participant stated she is confident in discussing her access to EAI data with students and has shared screenshots of their progress with them so they can measure their engagement against the average student. This creates an opening for her to follow up on any concerns and ensures she is transparent in how she uses it. She also had some concerns about how transparent she should be mainly because there is no specific guidance on this:

‘I have shared with a cluster team that I have done this, and my manager and colleagues thought it was a good idea so that has reassured me, and I would do it again, I think it would be good to have some official guidance for ALs to give them confidence to do this more.’ (P06).

The visual prediction of a student’s expected grade was one of the areas where some participants felt conflicted. Expectations were that participants would have concerns about being able to see grade predictions which might impact how they mark student assignments. Four participants (n=4) voiced confidence in their marking strategy all of these were experienced ALs and stated that they would not use grade predictions to influence how they marked assignments. One (n=1) participant (P03) who had only recently started to use EAI was not aware of this issue.

Two (n=2) participants (P08, P09) stated that they had concerns about the deterministic nature of grade predictions and one (n=1) participant (P08) stated that she does not look at the grade prediction as she is confident in her marking strategy.

‘I am very conscious about the fact that a computer is telling me what that predicted grades should be for student and I'm very uncomfortable with that. I don't
really like it. But I think if I didn't like it as much as I'm saying, I would probably hide it and I don't, but I don't use it consciously. (P08).

She also voiced concerns about ALs being able to see grade predictions, particularly for less experienced tutors who might not have developed the level of confidence necessary to trust their own judgement.

For two (n=2) participants (P04, P05) the grade prediction option had been removed from their dashboard view and one (n=1) participant (P10) who worked across two different faculties could see them on one module but not the other. Of the two (n=2) participants for whom the grade prediction function has been disabled one stated that she does not feel comfortable with it in case it becomes a limiting factor in how ALs mark assignments. The other stated that if he did have the option to look at it, he does not know if would influence his marking as he takes a very fine-grained approach:

'If I had a sense of what that student was, I'm not sure if that would sort of sneak in. I don't know how helpful or unhelpful that would be. It could be useful; for thinking about advice beforehand but when it comes to marking it, I think you do have to be quite focused on what you're looking at.' (P05).

There were also some reports of how it could be used positively. Two (n=2) participants (P08, P10) stated that they might look at the grade predictions but to see how they could build a strategy to improve a student's prediction for the next assignment:

I might use it more in terms of, right, that student is predicted a pass 4 and I think, hang on a minute let's work on that. Why is that student predicted a pass 4, what's going on, but I don't like being told that you know, somebody's going to get a pass 2 or a pass 3 or a pass whatever. I don't like that at all makes me very uncomfortable. (P10)

'I look at the grade prediction to see if it can help me to see how I might be able to work with someone to improve their grade. For example, if someone has been getting pass 2 grades and then suddenly, they are predicted a pass 3, that's a red flag for me so I will try to see if I can get them back to a pass 2.' (P08).

One (n=1) participant stated he did not find the grade prediction accurate and had concerns about using historical data to determine future outcomes. He stated that it does not allow for differentiation, for example a student who is studying a module which is easier for them than a previous module will most likely be predicted not to do as well in their current module based on a previous poor outcome:

I found that to be probably the less helpful side of it. I haven't found that as accurate. When it gets toward the end of the module, yeah, because you've got a couple of scores in there. But I think at the start it doesn't seem to be that helpful. You've got to be a bit careful about being led by historical data. We have access to student marks in other modules, so I think we've got to be careful about thinking, oh this is a pass 3 student, or this is a pass 2 student because that is putting your own view on it and that's not what learning is about. [.....] It needs to be totally objective.’ (P07).
4.9 Discussion of Findings from Semi-Structured Interviews

The following section discusses the findings from the semi-structured interviews (RQ1, RQ2).

4.9.1 Technology Use (Theme 1)

Using the UTAUT model (Venkatesh et al., 2003), performance expectancy (Chapter Two Section 2.5.3) is the level at which a person considers that the use of a new technology would help them to improve their work performance. It informs the behavioural intention of the user. One of the key factors in performance expectancy is the recognition that gender and age are significant factors relating to an individual ALs’ performance expectancy (Venkatesh and Morris, 2000). Following the model of UTAUT (Venkatesh et al. 2003) suggests that performance expectancy would influence behavioural intention to use the EAI dashboard more strongly for men than for women and particularly younger men. The findings indicate that gender has not had a specific influence on the use of the EAI dashboard in this study.

Regarding the use of technology in line with their roles as long-distance educators, all participants reported a level of expertise in navigating technology which was at least sufficient for their role. Some participants were familiar and confident with other technology use outside of their AL role. Examples given were, the use of Adobe Connect to deliver online tutorials which all participants used regularly to a required OU standard, Whilst all participants were comfortable in accessing and navigating EAI (albeit to different levels) there was recognition that other systems within OU which were mandatory (such as the Adobe Connect teaching platform) which had far-reaching influences on day-to-day teaching thus they were more likely to take precedence over ALs’ time than EAI. The main concern was that the OU has recently introduced a range of new technologies which need to be adopted (as discussed in Chapter One) as the OU has undergone substantial technology upgrades. As a result of this, EAI is not necessarily given the same level of attention as mandatory technological changes such as the use of the Adobe Connect and the electronic TMA marking system.

4.9.2 Data Use (Theme 1)

In relation to data literacy, self-efficacy as identified by Bandura (1982) and indicated in DTPB (Taylor and Todd, 1995) (Chapter Two Section 2.5.2) was high with all participants reporting that they felt comfortable managing data. All (N=11) participants reported confidence in using data in line with competencies expected in their AL role. There was some concern about working with graphs identified by one participant and as this is confidence in word processing programs in general, those participants who had done EAI training (P01, P02, P06, P11) were more able to navigate more nuanced aspects of the dashboard such as the selection of columns and interpretation of the prediction criteria.
4.9.3 Support Available to Use EAI (Theme 2)

Using DTPB (Taylor and Todd, 1995), experiences of the support mechanisms in place facilitate participants use of EAI. The normative beliefs in DTPB are those which shape the social norms therefore the approval of others such as management (superiors influences) or peers (peer influence) is fundamental to performing a given action (in this case using EAI). Additionally, the influence of others in the same situations (e.g., peers who also use EAI) alongside the motivation of the individual (e.g., ALs’ self-efficacy and volition) will also impact on intention. Therefore, it was expected that those ALs who are highly motivated and who are supported by peers and or management will have a higher intention to use EAI than those with less peer or management support or with less motivation to it.

Using UTAUT (Venkatesh et al., 2003) facilitating conditions determinants (whether the support needed to adopt a technology is in place) influenced intention to use EAI. The responses therefore fell into two main areas: Management support and peer support. As identified by Piderit (2000) and Armenakis, et al. (1993) (Chapter One Section 1.3) there are multiple reasons why employees might be unready to adopt new systems and why organisations may not support employees in accepting change. Evidence from this research shows that participants identified that they had limited support from management with some initial level of support which was not ongoing. Reasons for this were identified as managers having complex organisational responsibilities and EAI not being a priority particularly as it is not mandatory. Peer support was however identified by participants as an area where support was readily available and more easily accessible than organisational support and more informally addressed. Where some participants were motivated to use the EAI dashboard of their own volition, others found the lack of support more problematic particularly in maintaining a focus on its use given this was voluntary. There were also variations in the level of the support offered depending on whether a particular module team or faculty were promoting the use of EAI.

4.9.4 Barriers to Effective Use of EAI (Theme 3)

One of the themes emerging from the interviews was participants’ perceptions of the barriers to using EAI and the level of control they had to overcome barriers. Control beliefs are the extent to which the individual perceives that they have control over their intention to perform a behaviour (Ajzen, 1991). Being faced with barriers can lead to less perceived control if those barriers are not within the individual’s scope for change. Experience and confidence in using EAI meant participants were more able to overcome a perceived barrier. Expectations were that barriers to accessing EAI would influence intention to use it but that whilst some barriers were beyond the control of participants (e.g., decisions outside of their capacity to influence change) some would be within it (e.g., lack of understanding which could be remedied by training).
Those participants who used EAI regularly showed confidence in its ability to support students but the barriers that arose were concerns about the additional workload associated with checking the dashboard regularly and lack of payment for attending training sessions. Those participants for whom the dashboard gave restricted access to the functions also reported that they saw this as a barrier to effective use. Findings also support those of Herodotou et al. (2019c) who identified that systematic access of the OUAnalyse (OUA) short-term predictions by teachers might have limited the potential effectiveness that OUA interventions could offer students and that lack of support for teachers to adopt PLA influenced adoption.

4.9.5 Perceptions of EAI Usefulness (Theme 4)

Using the UTAUT model (Venkatesh et al., 2003) of performance expectancy (PE) determinants (the extent to which the user perceives the system as useful and how this will impact on behavioural intention). Venkatesh and Morris (2000) suggest that PE positively influences behavioural intent more for women than men. The demographic of OU ALs in the study and the parity in level of technology efficacy indicates that PE does not have a bias towards gender definition. Expectations were therefore that PE will have a positive effect on behavioural intention in the use of the EAI Dashboard. Experience of technology use identified in Section 4.9.1 will also be an influencing factor.

All participants could see the benefits of using EAI, however this was to a greater or lesser extent, dependent on how often they used it. Those who used it regularly were most likely to see it as useful. Those who did not use it regularly did not do so because they already had existing teaching strategies in place which they felt were sufficient to support their students.

Positive aspects of usefulness. Where most participants primarily focused on those students who are at risk of fail, some also look at supporting those students who are doing well but who could improve outcomes by finding patterns in behaviour which identified that although the student had been working to a high standard, their standards had slipped somewhat and those tutors who used it regularly were more likely to contact those students. Yet, those other strategies were shown to be less effective compared to using the EAI dashboard to monitor students and respond to those at risk (Herodotou et al., 2019c).

Concerns of the usefulness. As seen by Wolf et al. (2013) clicking behaviour on the VLE dashboard is not necessarily in itself an indicator of outcome, as they found that some students’ behaviour was such that they would have periods of inactivity online and spurts of activity prior to an assessment deadline and still pass and still do well on their module which was also identified by Hlosta et al. (2020). Those participants who used the dashboard regularly were able to identify these patterns of behaviour and were more confident in accepting that students work in different ways recognising that high levels of activity do not always correlate with best outcomes and vice versa. The OU also has a
specific demographic of students (Chapter Three Section 3.3.2) many of whom work in clusters of time to be able to fit in their studies around their work and family lives.

4.9.6 Perception of EAI Accuracy (Theme 5)

Performance Expectancy is the extent to which the user perceives the system as useful in UTAUT (Venkatesh et al., 2003) and how this will impact on behavioural intention to use EAI. Expectations were therefore that if participants did not consider that the system was accurate, they would not find it useful.

Concerns about the accuracy of EAI data were evident for example if students downloaded the data in advance this would show that they were not active on the VLE when they were working but offline and questions as to whether being online was a clear indication of student activity. This appeared to be an issue across several areas of the questions asked. It was addressed in the theme relating to the accuracy of the dashboard and in perceptions of the usefulness. There was acceptance that data was not always going to be accurate and that circumstances beyond what is achievable identified using algorithmic information can occur (such as family crisis preventing engagement in the module). (Hoel and Chen, 2018; Hlosta et al., 2017 Hlosta et al., 2020’ Kuzilek et al., 2015). Where there were differences in opinion, was in how far this mattered.

Participants who were regular users of the dashboard were more likely to be able to mitigate algorithmic inaccuracies by understanding the parameters within which algorithms work.

4.9.7 Ethical Use of Data (Theme 6)

From the literature review in Chapter Two it was identified that no theoretical model addressed the ethical use of PLA. Yet the interview data of this research showed that this was an issue of concern for participants. The ethical use of student data was discussed in detail by all 11 (N=11) participants and was the question which generated the most responses as can be seen in the coding sequence table (Section 4.2.1 Table 6). Where some participants spoke directly about the use of student data to generate algorithms, others had concerns about the wider use of student data and how far students were giving informed consent for their data to be used for PLA (Chapter Two, Section 2.4.1). There was a mix of ideas regarding ethics ranging from, the expectation that the OU should use all opportunities and data systems available to support students to significant concerns about how far students were aware that their data was being used to monitor their progress.

Another ethical concern was the implications of having access to predictive grades and how far this would influence how ALs grade students’ work. Some participants stated that they did not look at grade predictions and that they did not allow this to influence their marking; others stated that seeing the predicted grade was helpful to them whilst others
did not have this data available to them as it had been removed from their view by either their module team or faculty to prevent the risk of marking bias.

What was also evident was that even though there are clear ethical guidelines available to staff and students, a significant number of participants were not aware of these policies or had not read them therefore it is not possible to fully understand whether more engagement with the ethical policy guidance would alter participants’ perception at this stage and more investigation into the ethical basis of using EAI is needed.

The following table outlines a summary of the findings of the analysis discussed based on the determinants of the theoretical models used to inform the RQs as well as identifying findings which have emerged from the analysis which is not captured by any of the determinants of the theoretical models (Table 7).
<table>
<thead>
<tr>
<th>Table 7 Summary of Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>TPB</strong></td>
</tr>
<tr>
<td>Technology Use and Data Literacy in Everyday Life</td>
</tr>
<tr>
<td><strong>Attitude</strong></td>
</tr>
<tr>
<td><strong>Subjective norms</strong></td>
</tr>
<tr>
<td><strong>Perceived behavioural control</strong></td>
</tr>
</tbody>
</table>

Leading to
<table>
<thead>
<tr>
<th>Beliefs</th>
<th>About the outcome of performing the behaviour Expectations of others and the availability of resources available to carry out the behaviour</th>
<th>Participants showed evidence of a belief that was useful to help them in their role and the adoption of technology was positive</th>
<th>Belief that the use of EAI was by personal volition rather than organisational support</th>
<th>More organisational support and training would be effective to support use</th>
<th>Overall perception that EAI could be useful but with acknowledgement that it has limitations</th>
<th>EAI forms part of the picture for supporting students but does not replace existing teaching approaches</th>
</tr>
</thead>
<tbody>
<tr>
<td>DTPB</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Self-efficacy</td>
<td>The motivation to use based on self-belief in affecting change</td>
<td>Self-efficacy in technology was high</td>
<td>Most participants were self-motivated to use EAI</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Compatibility</td>
<td>How far PLA is compatible with existing teacher beliefs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UTAUT</td>
<td>Performance expectancy</td>
<td>The level at which a person considers that the use of a new technology would help them to improve their work performance</td>
<td>Using EAI can positively influence outcomes</td>
<td>Performance expectancy had a positive effect on behavioural intention in the use of EAI predominantly with students at risk of non-submission</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Effort expectancy</td>
<td>The extent to which the user perceives the system as easy to use and how this will impact on behavioural intention</td>
<td>Level of Effort expectancy indicated that EAI and the dashboard was easy to use and positively influenced behavioural intention</td>
<td></td>
<td></td>
<td>Perceptions of the accuracy of data influenced the extent to which these affected participants perceptions of usefulness</td>
<td></td>
</tr>
<tr>
<td>Facilitating conditions</td>
<td>The degree to which the user believes that the organisational conditions and readiness are adequate for effective use of the system</td>
<td>Organisational readiness is not in place to facilitate using PLA to support students</td>
<td>Facilitating conditions were not sufficiently robust to encourage use of EAI</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social influence</td>
<td>The degree to which the user perceives others (who are important</td>
<td>Social Influence had an impact for some participants using EAI</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Findings emerging from data but not captured by existing models

<table>
<thead>
<tr>
<th>Grade prediction</th>
<th>Lack of support for understanding the ethical use of student data but needs to be measured against the lack of engagement with EAI policy documents</th>
<th>There were differences of access to EAI based on different faculty decisions and some participants did not see grade prediction data</th>
<th>Some participants reported that they chose not to look at grade predictions as they saw it as having ethical implications for how work was graded.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data privacy</td>
<td></td>
<td></td>
<td>Scepticism about the knowledge students hold on the data held about them. Concerns that predictions of grade might influence approaches to marking TMAs</td>
</tr>
</tbody>
</table>

Table 7. Summary of findings using TPB DTPB and UTAUT.
4.10 Conclusion

Eleven (N=11) semi-structured interviews have been analysed using a thematic approach with the identification of six themes which form the data for Study One. The interview data has shown the responses of participants’ knowledge of technology, perceptions of the support available to use EAI, the barriers faced in using it and their beliefs about the usefulness and accuracy of EAI. Findings show a mixed approach to beliefs about the use of PLA and evidence that participants have a widely varying approach to using PLA in the form of the EAI dashboard.

Study One has addressed one of the main areas of concerns in the adoption of EAI use which is the ethical position of the University in relation to the use of student data and use of grade prediction. Theoretical models have looked at technology use and behaviour in relation to existing technologies and have been useful in guiding the understanding of (RQ1 RQ2) however they do not specifically address PLA and there are areas which are not supported by existing theoretical models. From this research there is scepticism about the knowledge students hold on the data that is held about them. Further to this there were mixed feelings about the ethical use of predictions particularly where grades are predicted and whether these may impact on teacher decisions about how to grade students’ work.

From this study I consider whether behavioural and technology models now need to consider PLA in a different light to include determinants which will take account of predictive data and their influence PLA adoption. Whilst there is a wealth of information regarding the ethical use of data (Chapter Two Section 2.4) incorporating this into a model of PLA use would add to the existing understanding of PLA use and why there might be resistance/unreadiness to use it.

Chapter Five now moves forward to address RQ3. Study Two looks at the actual use of six (N=6) participants and their actual use of the EAI dashboard using eye-tracking technology. Study Three looks at the actual use of Five (N=5) participants who carried out the same task using screen-sharing without eye-tracking metrics applied.
Chapter 5 Study Two: Eye-Tracking and Study Three: Screen-Sharing Observations

5.1 Introduction

Chapter Five aims to address RQ3 through observations of six (n=6) of the 11 participants using eye-tracking and Retrospective Think Aloud Protocols (RTAP) and five (n=5) of the 11 using Concurrent Think Aloud Protocols (CTAP).

3) What are Associate Lecturers’ (a) perceptions of the use and usability of PLA and (b) actual use as measured by fine-grained eye-tracking approaches?

Section 5.2 addresses the interview structure for the eye-tracking observation with explanation of the visual data used to collect data (gaze plots and heat maps). In Section 5.3 the findings of the visual data are discussed using the Areas of Interest (AOIs) to observe participants’ use of the Early Alert Indicators (EAI) dashboard and the duration of time spent on each AOI. Covid-19 restrictions meant it was not possible to continue with face-to-face research six (n=6) participants had taken part in the eye-tracking study before it was no longer possible to continue. To mitigate some of the impact of this, the remaining five (n=5) participants agreed to carry out an online screen-sharing activity where observation was possible, but without the capacity to use the metrics applied to the eyetracking data. The screen-share observations and CTAP interviews are discussed in Section 5.4 with the same AOI data (but without the metrics applied as eye-tracking could not be used). Section 5.5 summarises the findings from both Study Two and Study Three before concluding the chapter in Section 5.6.

Both the semi-structured interviews and the eye-tracking observations were carried out on campus at Milton Keynes prior to the lockdown restrictions in March 2020. The sample of participants were Associate Lecturers (ALs) who had used EAI at least once. Experience and frequency of use varied to get a broad range of comparisons (histogram data for all 11 (N=11) participants in Chapter Four, Section 4.5 Figure 20).

5.2 Study Two Eye-Tracking Observations

The session started with the eye-tracking observation, followed by RTAP interviews where recordings were played back for participants to talk through their actions and choices (see Chapter Three Section 3.6.2 for detailed methodological description of this approach). The semi-structured interviews (discussed in Chapter Four) were then conducted. A test session was conducted with a colleague to test the equipment and particularly the calibration process and the impact of using two web pages and the functions necessary to record the session and playback quality. From the pilot study, the AOIs were identified,
and metric statistics were applied to ensure that data could be collected for analysis. On satisfactory completion of this test, the main study interviews were conducted with six (n=6) participants to develop a more fine-grained understanding of how ALs use EAI.

To carry out the observation, participants were seated comfortably roughly 70cm from the computer screen. Firstly, they carried out a 9-point eye-tracking 182 calibration. Once the calibration was completed, participants were asked to observe the anonymised version of the EAI dashboard. All six (n=6) participants met the threshold to participate with a small screen drift from one participant but not sufficient to exclude the data. Each participant viewed the same data for consistency. On the EAI dashboard, some filters are available to change the page view. Each filter was set to the same parameters for consistency, although participants could change these to demonstrate which ones they use and their preferred visualisation. The pace was self-defined, and participants were asked to finish the session by pressing the escape button.

5.2.1 Gaze Plots

Gaze plots show the location, order, and time spent looking at locations on the stimulus, in this case the web pages of the EAI. The gaze plot provided a time sequence as well as the time spent looking at the stimuli, which is shown by the diameter of the fixation circles. The longer the look, the larger the circle. See example below (Figure 21).

Figure 21. Gaze plot example of the time sequence and location of the fixations on a stimulus.

During the interview and when playing back the recording, a moving red circle represented each fixation point. The size of the dot increased with the length of fixation at
that point. To ensure clarity and accuracy, the recording of the engagement by each AL was played back to them at half speed and paused at intervals to stimulate discussion in line with recommendations from Cho et al., (2010) who noted that it was during video playback that participants were more likely to identify where they were uncertain about tasks rather than whilst carrying out the task. Questions were structured around allowing participants to discuss each point from their own perspective for example, ‘there appears to be a sustained focus on this area could you tell me more about why this is?’ In some cases, the sustained fixation was related to interest in a particular AOI and in other situations it was an exploration because of uncertainty of its meaning. Therefore, asking open questions and avoiding the use of terms such as ‘why was this of particular interest?’ was important in ensuring the most accurate responses. Participants were able to see the gaze plot data during playback and this formed the focus of the RTAP questions (Eye-Tracking Demo).

5.2.2 Heat Maps

Heat maps use different colours to show the density of the fixations participants made in certain areas of the image or for how long they fixated within that area. Red indicates the highest number of fixations or the longest time, and green the least, with varying levels in between. Heat maps show how looking is distributed over the stimulus. In contrast to the gaze plot, there is no information about the order of observation of stimuli in a static heat map and the focus is not on individual fixations. Heat maps have been found to be particularly useful in identifying areas requiring further analysis but less so as an analytic tool (Blaschek et al., 2014). Whilst heat maps have been used extensively in eye-tracking studies, for this research they proved useful for providing a quick guide to the overall picture of each participant’s gaze but were less useful for in-depth analysis (Figure 22). Using a heat map was a way in confirming which AOIs would be most useful and that no significant areas were missed. To this end examining the heat maps of each participant was a method of ensuring validity.
Figure 22. Heat map example indicating the density of gaze on given stimuli.

5.2.3 Areas of Interest

As identified in Chapter Three Section 3.7.2, in line with recommendations from the method of analysis for this research focuses on AOIs which allow for the calculation of quantitative eye movement measures. These can include fixation counts and durations, identified within the AOI boundary over the time interval of interest. Due to the density of the data set for this study and as the data is across two web pages with options to change the data view, specific AOIs were defined during the analysis based on the main areas of the EAI dashboard and were calculated according to the mean of the overall visit duration in seconds to each AOI. These were broken down as follows:
VLE Activity: the first half of the first page shows data of all students on the module and their average activity on their virtual learning environment (VLE). It compares the average VLE click activity using graph lines and the average assessment score using columns and measures these against the previous year. (Chapter One Section 1.2.1 Figure 1).

Tutor group data: The next AOI looks at the tutor group (TG) data which is specific to each AL. This AOI shows the legend of explanation and the overall tutor group for each participant. The first column shows student information including past marks awarded for submitted assignments and predictions as to whether they are likely to submit their next assignment. The second column shows the short-term predictions (next TMA predictions) and likelihood risk of non-submission including the blue bar visual (the longer the bar the higher the % risk of non-submission). The third column shows the long-term the percentage likelihood of the student completing the module. ALs can choose to ‘select columns’ to choose their preferred view which will either hide or add columns (Chapter One Section 1.2.1 Figure 2).

Individual Student: This AOI looks at individual student data which gives an overview of their VLE activity, and their individual assignment score compared to the average students in the same year. Individual students can be viewed by clicking on their name from the tutor group list. It shows their long-term prediction of completing and passing the module and their short-term predictions with information on how the predictions are calculated (Chapter One Section 1.2.1 Figure 3 and 4). In this research four students were viewed (shown as Std A, Std B, Std C and Std D on Table 8).

5.3 Duration of Time Spent on AOIs

The following section addresses the findings from the eye-tracking data to identify which parts of the EAI dashboard were used the most. It illustrates the overall picture of three main AOIs: The VLE data, the tutor group information and the individual student data. The mean time in seconds spent visiting each AOI is plotted on Table 8 indicating the trajectory of the visits. Table 9 summarises the overall time spent and the number of visits to each AOI in a more simplified form. The mean duration in seconds spent on each AOI varied amongst participants as did the trajectory of visits and the number of individual students viewed and are discussed in Sections 5.3.1-5.4.3.
Table 8. To give the mean average of the duration of time in seconds spent on each AOI

Because the process is not linear, and some participants made several visits to an AOI subsequent visits are also recorded. For example, P05 looked at the VLE AOI five different times whereas P06 looked at it twice, therefore each AOI has a corresponding number to clarify this (e.g., VLE1 is the first visit and VLE2 VLE3 VLE4 VLE5 VLE6 are subsequent revisits). Student A B C represent the only three students who were chosen by participants (from the tutor group list) and the division line represents subsequent visits where a participant looked at the student more than once. (For example, P01 viewed Stds A and C twice. P06 viewed Std C once)

<table>
<thead>
<tr>
<th></th>
<th>VLE1</th>
<th>VLE 2</th>
<th>VLE 3</th>
<th>VLE 4</th>
<th>VLE 5</th>
<th>VLE 6</th>
<th>TG1</th>
<th>TG2</th>
<th>TG3</th>
<th>TG4</th>
<th>TG5</th>
<th>TG6</th>
<th>TG7</th>
<th>TG8</th>
<th>Std A</th>
<th>Std B</th>
<th>Std C</th>
</tr>
</thead>
<tbody>
<tr>
<td>P01</td>
<td>27.87</td>
<td>7.64</td>
<td>31.63</td>
<td>8.6</td>
<td>-</td>
<td>-</td>
<td>1.59</td>
<td>2.59</td>
<td>1.75</td>
<td>2.79</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>12</td>
<td>16.06</td>
<td>-</td>
<td>47.03</td>
</tr>
<tr>
<td>P02</td>
<td>0.98</td>
<td>4.08</td>
<td>6.41</td>
<td>1.15</td>
<td>4.31</td>
<td>8.34</td>
<td>6.16</td>
<td>6.49</td>
<td>11.99</td>
<td>12.81</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>4.39</td>
<td>4.99</td>
<td>7.77</td>
<td>9.97</td>
</tr>
<tr>
<td>P03</td>
<td>117.66</td>
<td>128.73</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>10.4</td>
<td>10.87</td>
<td>-</td>
<td>-</td>
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<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>P04</td>
<td>48.04</td>
<td>56.87</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>4.9</td>
<td>5.19</td>
<td>-</td>
<td>-</td>
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<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>P05</td>
<td>4.61</td>
<td>35.25</td>
<td>15.09</td>
<td>40.54</td>
<td>5.47</td>
<td>17.68</td>
<td>13.4</td>
<td>3.62</td>
<td>0.27</td>
<td>3.81</td>
<td>15.74</td>
<td>4.0</td>
<td>0.27</td>
<td>4.4</td>
<td>50.27</td>
<td>58.37</td>
<td>-</td>
</tr>
<tr>
<td>P06</td>
<td>59.45</td>
<td>69.94</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>1.87</td>
<td>2.4</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Legend

P = Participant
VLE = Virtual Learning Environment observed on page 1
TG = Tutor Group observed on page 1
Std = Individual students on page 2 (chosen from the Tutor Group list)

Table 8. Mean duration of time spent on each AOI in seconds.
Table 9 has summarised the data from Table 8 to give a more overall picture of the time spent on each VLE (for example, we can see from this table that two participants did not look at the individual student data on page two). We can also see at a glance the overall mean time in seconds spent on each AOI and the findings relating to these data are discussed in sections 5.3.1-5.3.3.

Table 9. Total mean time in seconds spent on each AOI for each participant

<table>
<thead>
<tr>
<th>Participant</th>
<th>Page 1. Overall Cohort VLE: Total Duration of Visit in Seconds</th>
<th>No of Visits to page 1 VLE</th>
<th>Page 1. Tutor Group Total Duration of Visit in Seconds to include short- term and long- term predictions</th>
<th>No of Visits to Tutor Group Page 1</th>
<th>Page 2. Ind Std Total Duration of Visit in Seconds</th>
<th>No of Visits to Ind Std Page 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>P01</td>
<td>75.74</td>
<td>4</td>
<td>8.72</td>
<td>4</td>
<td>128.38</td>
<td>4</td>
</tr>
<tr>
<td>P02</td>
<td>25.27</td>
<td>6</td>
<td>37.45</td>
<td>4</td>
<td>59.79</td>
<td>6</td>
</tr>
<tr>
<td>P03</td>
<td>246.39</td>
<td>2</td>
<td>21.27</td>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>P04</td>
<td>104.91</td>
<td>2</td>
<td>10.09</td>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>P05</td>
<td>118.64</td>
<td>6</td>
<td>45.51</td>
<td>6</td>
<td>108.64</td>
<td>2</td>
</tr>
<tr>
<td>P06</td>
<td>129.39</td>
<td>2</td>
<td>4.27</td>
<td>2</td>
<td>44.65</td>
<td>2</td>
</tr>
</tbody>
</table>

Table 9. Total time for each participant spent on each AOI.

5.3.1 VLE on Page 1

All participants spent time looking at the VLE, P02 and P05 looked at the VLE page six times, whereas one (n=1) participant (P01) viewed it four times and three (n=3) participants (P03, P04, P06) viewed it twice.

Three (n=3) of these participants (P06, P03, P04) made fewer visits but spent a lot of time on the first visit analysing the graph data and stated that this was because they needed to remind themselves of the functions.

‘I usually look at this to refamiliarise myself with the dashboard. I can see (on the playback) that the red circle has really focused on this. That makes a lot of sense as it has taken me a while to remember what it means.’ (P03).

From the RTAP and semi-structured interviews one (n=1) participant (P05) identified being confident in technology use and was able to negotiate the EAI dashboard without any problem despite not having attended training or looking at the training documents on the website. As the VLE data on this page does not give information about individual students or the participant’s tutor group, it was expected that this would be the least useful part of the dashboard, but this was not the case. For P01 who was confident in her use of
EAI the VLE was viewed more out of curiosity than usefulness as she liked to see the overall picture as it gave her an idea of module content and whether there were significant changes from year to year:

‘I’m very comfortable with this part of the dashboard, it’s measuring this year’s overall cohort with last year. It’s not the part of the dashboard I use the most, but it’s good to be able to see whether there is a trend. It’s usually pretty similar but I’d like to know if there was anything that might affect it such as whether the module content has changed. It’s more curiosity than anything.’ (P01).

Similarly, another confident user (P02) found it useful to understand the module as a whole and both P01 and P02 were able to read the data quickly without needing to address the legend to remind them of its function. There were also misconceptions about the VLE as one (n=1) participant (P06) believed that it was a comparison of her current tutor group activity to her tutor group of the previous year, therefore time spent looking at the VLE was not providing her with the data she believed it to be. However, she was a regular user of EAI and found it useful.

‘The first thing I am doing is that I am looking at the lines and the columns. The brown ones I think are my tutor group and the blue ones I think are the rest of the cohort, so I am looking at the spaces between the lines to see if my group are performing as well as the rest of the groups. I am also looking at the columns for the TMA scores to see if mine are similar.’ (P06).

For this AOI time spent looking at the data was shorter for participants who understood the dashboard well as they could quickly assess that they would benefit from concentrating on more useful areas.

**5.3.2 Tutor Group on Page 1**

Having looked at the VLE the next area of the EAI dashboard is the tutor group where participants were able to view a tutor group showing the demographic details of the student (personal identifier name) and their previous TMA marks and their predictions for the submission of the next TMA as well as their percentage likelihood of completion and passing the module.

Due to the density of data within the overall tutor group, three specific AOIs were identified within the Tutor Group AOI to develop a better understanding of which specific objects were viewed. These were broken down into three areas to give a more nuanced understanding of the areas visited (Chapter Three Section 3.7.2 Figure 17). Firstly, the student group data where participants can see their overall student group. Secondly, the short-term predictions as to whether a student is expected to submit their next assignment. Thirdly, the long-term predictions as to whether the student is likely to pass and complete their module. Table 10 summarises the mean average of the total visits to
each AOI within the tutor group which shows that all participants looked at the student group data once except P05 who made three subsequent visits. P05 was also the only participant to make subsequent visits to the short-term predictions.

Figure 23. Example of the focus of attention on the tutor group AOI

As identified in Table 8, the tutor group AOI was visited eight times by one (n=1) participant (P05) and four times by two (n=2) participants (P01, P02) and twice by three (n=3) participants (P03, P04, P06). Both P03 and P04 were less regular and confident in their use of EAI. The most viewed areas within this AOI were the student scores and the short-term predictions as to whether they would submit and pass their next assignment with less attention to the long-term predictions. Despite the option to select different columns which would have given more data only two (n=2) participants (P01, P02) did this to look at the student’s last log in date. The RTAP interviews identified that these were the only two participants that were aware that this was an option.

‘Usually once I have set up the columns, I don’t have to look at them again. I take off the staff tutor column as that is of no use to me, but I like to be able to see the week that the student last logged in. That’s a quick way of seeing if they are online. If I can see they haven’t been on for a week or more I will look more deeply into that. I’ll click on their individual data and see if their prediction has changed and whether there is anything to be concerned about’ (P02).

From the tutor group view the consensus among all participants (n=6) was that the traffic
light visual was easy to read:

‘Graphs are okay for me but there’s certain ways of learning that are easier. This (traffic lights) is more visually interesting and clearer for me. So, this is the bit that I kind of look at. So, I look at the TMA scores and I look at the non-submits. I look at this area a lot.’ (P03).

“I think it’s this part is self-explanatory I don’t need to look at the legend, with the traffic light system it’s easier to understand than the graph’ (P04).

Table 10. Mean average of the total visit duration of each section of the tutor group AOI in seconds

<table>
<thead>
<tr>
<th>Participant</th>
<th>Student Group 1</th>
<th>Student Group 2</th>
<th>Student Group 3</th>
<th>Student Group 4</th>
<th>Short Term 1</th>
<th>Short Term 2</th>
<th>Short Term 3</th>
<th>Long Term 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>P01</td>
<td>6.63</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>1.93</td>
<td>-</td>
<td>-</td>
<td>0.16</td>
</tr>
<tr>
<td>P02</td>
<td>44.46</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>1.22</td>
<td>-</td>
<td>-</td>
<td>2.08</td>
</tr>
<tr>
<td>P03</td>
<td>17.71</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>1.66</td>
<td>-</td>
<td>-</td>
<td>1.9</td>
</tr>
<tr>
<td>P04</td>
<td>4.13</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>3.16</td>
<td>-</td>
<td>-</td>
<td>2.8</td>
</tr>
<tr>
<td>P05</td>
<td>8.76</td>
<td>10.4</td>
<td>3.92</td>
<td>4.4</td>
<td>0.84</td>
<td>30.6</td>
<td>0.21</td>
<td>3.16</td>
</tr>
<tr>
<td>P06</td>
<td>2.15</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>1.56</td>
<td>-</td>
<td>-</td>
<td>0.56</td>
</tr>
</tbody>
</table>

Legend

Student Group = Mean of total visit duration in seconds to student group data (Student Group 1 is the first visit and Student Group 2 and 3 are subsequent revisits)

Short-term = Mean of total visit duration in seconds to short-term (OUA) TMA predictions and scores. (Short-Term 1 is the first visit and Short-Term 2 and 3 are subsequent revisits)

Long-term = Mean of total visit duration in seconds to Long-Term (SPM) data

From the data information the most viewed area of the tutor group data was the student group information and the predicted likelihood of submitting their next assignment. The data shows that participants concentrated on the short-term (OUA) data and less attention was paid to the long-term (SPM) data. The most viewed area within the short-term predictions was the prediction indicators. All participants looked at these however whilst they were well understood by four (n=4) participants (P01 P02 P05 P06) two (n=2) (P03, P04) were uncertain of their meaning and whether the blue bar percentage indicator showed that the higher the percentage the higher the likelihood of non-submission or vice versa. Further concerns were noted by two (n=2) participants (P02 P06) regarding the
brevity of the predictor explanations which were limited. For example: ‘The prediction indicators are a bit ambiguous: This one says the prediction is based on the student’s activity in week 2 but is this saying the activity was good or not? I think it needs to be clearer.’ (P02).

On further examination through RTAP discussions the overall findings showed that this was because long-term outcomes were influenced by the actions taken to improve the short-term outcomes thus it was through acting on the short-term predictions that long-term outcomes could be improved. Two (n=2) participants (P04, P05) stated that they had never seen the long-term predictions before as they are hidden on their view of the dashboard. Whereas one (n=1) participant (P04) did not think they would be useful, one (n=1) participant (P05) thought that they might be:

‘On the module that I teach I don’t see the long-term predictions, but I’m interested in them as this is the first time, I’ve seen them. It might be interesting to have that level of detail.’ (P05)

Concerns also about how beneficial the long-term predictions are were voiced:

‘I don’t look at them really because I haven’t found them to be reliable. I’ve had students who according to the long-term predictions have only a 10% chance of completing and I know the student and I know they will be OK.’ (P02).

One (n=1) participant (P01) stated that she saw the long-term and short-term predictions as akin to a long- and short-range weather forecast. Therefore, viewing the data in conjunction with each other did give a wider picture, although as the long-term predictions are only updated at given points, it was not necessary to focus on them at other times. Likewise, P02 stated that she was more likely to look at these predictions closer to each fee liability point as this is when the data changes.

5.3.3 Individual Student on Page 2

Having viewed the AOIs on page one, participants then made decision as to which students they wanted to view individual data for. There was no specific remit for this, participants were asked to use the dashboard in whatever way they would find it most useful to them. To access the individual student view, participants could click on the student’s name to change the dashboard view. The individual student data was viewed by four (n=4) participants, with two (n=2) stating that they were not aware that they could drill down from the tutor group page to look at individual students.

To gain a deeper understanding of the areas within the individual student AOI, three areas were identified: Firstly, the individual student’s activity on the VLE (Figure 24); Secondly, the short-term predictions (TMA predictions and scores) (Figure 25); Thirdly, the individual long-term predictions as shown in Figure 26. Table 11 outlines the mean time in seconds spent on each area by the four participants who accessed this function.
Table 11 individual students’ short-term and long-term predictions

<table>
<thead>
<tr>
<th>Participant</th>
<th>Ind Std VLE 1</th>
<th>Ind Std VLE 2</th>
<th>Ind Std VLE 3</th>
<th>Ind Std ST (OUA) Predictions 1</th>
<th>Ind Std ST (OUA) Predictions 2</th>
<th>Ind Std LT (SPM) Predictions 1</th>
<th>Ind Std LT (SPM) Predictions 2</th>
<th>Ind Std LT (SPM) Predictions 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>P01</td>
<td>71.27</td>
<td>39.6</td>
<td></td>
<td>12.84</td>
<td>3.58</td>
<td>1.09</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>P02</td>
<td>39.93</td>
<td>12.08</td>
<td>5.87</td>
<td>0.28</td>
<td>-</td>
<td>0.43</td>
<td>1.03</td>
<td>0.17</td>
</tr>
<tr>
<td>P05</td>
<td>93.21</td>
<td>-</td>
<td>-</td>
<td>11.56</td>
<td>-</td>
<td>3.87</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>P06</td>
<td>30.66</td>
<td>-</td>
<td>-</td>
<td>12.57</td>
<td>-</td>
<td>1.42</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Legend

Ind Std VLE = Mean of total visit duration in seconds to the individual student’s VLE activity VLE 1 is the first visit, VLE 2 and 3 are subsequent revisits

Ind Std ST (OUA) predictions = Mean of total visit duration in seconds to the individual student’s short-term predictions (TMA predictions and scores) (Ind Std ST(OUA) 1 is a first visit, Ind Std ST (OUA) 2 is a subsequent visit)

Table 11. Mean time of duration in seconds of visits to individual students’ VLE activity.

Figure 24. Example of the focus of attention on the individual student AOI (VLE)

This figure shows an example of the focus of attention for an individual student. The large red circle indicates that the participant is looking at the student information for the present week (14) where there is a spike in activity (indicated by the brown trend line). From the data we can see that the student has below average engagement on the VLE compared with the average student on the module but is still active.
Figure 25. Example of the focus of the individual student AOI Short-Term Predictions; TMA Predictions and Scores

This figure shows the view that participants could see when they look at individual student data. This example shows the focus of attention is the data which explains what the student’s short-term prediction of the likelihood of submitting their next TMA is based on.

Figure 25. Example of the focus of the individual student AOI short-term predictions.
Figure 26. Focus of Attention on the Individual Student AOI Long-Term predictions

This figure shows the view that participants could see when they look at individual student data. This example shows the focus of attention. It is the data which explains both the student’s short-term prediction of the likelihood of submitting their next TMA. The focus also moves to show that the participant is also looking at the likelihood of the student passing the module based on their long-term predictions which are updated at four points across the module.

Figure 26. Example of the focus of attention on the individual student AOI long-term predictions.

Three (n=3) participants looked at the only student (identified as Std C in Table 8) who was predicted not to submit their next assignment. RTAP interviews identified that these participants chose to look at this student to see if there was anything they could do to support them such as give an extension or refer them for additional support to the student support team. What was evident on the VLE activity for student C was that despite the poor prediction, the student was still showing activity on the VLE. Three (n=3) participants identified therefore that by looking at the VLE data, this was a student for whom they could intervene in a timely manner to offer additional support.

‘They might be a ‘ghost’ student. So, I’ll just click on that to see. I can see this student has engaged at some point because there’s peaks, although there’s inactivity for the majority. There was quite a lot of activity there. So yeah, so it gives me an idea that the student exists […]. I would certainly have an alert on my records for this student as needing a bit more support. But I’m a bit more reassured now.’ (P02).

One participant did not choose to look at this student and the RTAP interview identified that the participant assumed that this was a student who was not active on the module and therefore chose to look at other students who were active but showing low scores:

‘There is not a lot you can do to rescue the person who is showing red they haven’t submitted, and they are unlikely to submit TMA 02 it feels as though they have
gone but the one that is showing green the report suggests that they are struggling a bit and they might need some extra support. So, this is the second highest risk student but there is the likelihood of being able to help them but the student who is showing red is probably not going to be able to be helped at this stage now’ (P05).

Similarly, P01 and P02 also identified a student with low scores and indicated that this would be a student for whom early intervention would help, not only in terms of maintaining engagement but also in raising their grade to improve their outcome.

Overall, findings showed that of the four (n=4) participants who looked at individual student data, the VLE data was the feature viewed the most.

RTAP interviews identified that all four (n=4) participants saw VLE as the most useful data as they could see immediately if the student was still engaged and how their progress compared to the average student:

‘This is the most useful part of the dashboard for me. Being able to see a student’s individual actions is where I know I can really make a change. The things that I mostly look at are how my tutor group is performing and whether individual students are struggling and need additional help.’ (P06).

They also stated that it was useful to be able to see assessment scores and an overview of when the next assignment was due for submission. The VLE data was the main driver for contacting a student (if they were not fully active). Individual short-term predictions were viewed more than the long-term predictions with the same rationale as for the tutor group data; that they were useful for an overall picture of the student, but they did not provide the same level of detail as the short-term data and were not updated as frequently.

The following section looks at Study Three which was the screen-share observations which were conducted when face-to-face interviews were no longer possible due to Covid-19.

5.4 Study Three: Screen-Sharing Observations

This section addresses the analysis of the screen-sharing observations with five (n=5) participants. These participants viewed the same version of the EAI dashboard set to the same anonymised data and dashboard settings. The interviews took place using MS Teams. To maintain confidentiality, I shared my screen and gave each participant the right to ‘take control’ and use the screen accordingly. Prior to the study a pilot session took place with a colleague to test MS Teams as a platform and to test the ‘take control’ facility. From the pilot, it was identified that using RTAP was time consuming: it meant downloading and reopening the recording and the process was longer than could be expected by participants as well as not within the time scale agreed with the Human Resources Ethic Committee. It was found that recall without stimulus led to uncertainty in
accurately reporting the actions taken. Given these concerns, CTAP interviews were conducted, and participants were asked to place their cursor over the areas they were viewing. Whilst this did not give the depth of detail that eye-tracking gave, there were useful insights from the interviews as discussed below.

5.4.1 VLE on Page 1

Observations of the VLE (Study Three) were in line with the reported experiences of the participants in the eye-tracking study (Study Two) with participants briefly looking at this data but more out of interest than intention to act upon. One (n=1) participant (P11) identified themselves as someone who has an interest in data interpretation. He would look at the overall VLE activity but more out of curiosity and to see whether there were any significant changes from the previous year, but as he does not find it particularly relevant to his own students so would only look at it briefly. One (n=1) participant (P08) reported that she quickly scans the VLE activity and finds it useful to be able to see when the next assignment is due to be submitted. One (n=1) participant (P07) uses the VLE data to measure his average assessment scores against the average on the VLE graph as a form of quality assurance that his marking is broadly within the mean average of the overall student cohort scores. There was an error of understanding by one (n=1) participant (P08) as to what the VLE graph represented who thought that the graph showed their individual student data measured against the national cohort.

5.4.2 Tutor Group on Page 1

Observations of the tutor group area of the dashboard were broadly similar to those of the eye-tracking observations with four (n=4) participants focusing on the student group data initially (Figure 24 section 5.2.3). One (n=1) participant (P08) looked at the short-term predictions on the tutor group page to identify students at risk before looking at the student group and choosing to look at the student who was identified as at risk of non-submission based on that data. All participants reported that they found the short-term predictions more useful than the long-term predictions (as with the findings from the eye-tracking). It was considered that the long-term predictions were not something participants had control over other than by using the indicators of the short-term predictions to engage with students at risk and improve their long-term outcomes. One (n=1) participant (P07) described the long-term predictions as being like ‘a weather forecast for weather you are already having.’

Conversely, one (n=1) participant (P08) stated that she did find the long-term predictions useful in that if she could see that they have changed significantly from the last update, it would prompt her to look at the student’s progress to see what had changed. They were considered as secondary data to the short-term predictions as these were data she could use to make changes to a student’s outcome.

One (n=1) participant (P11) stated that he looks at the student group to identify those
students who appear to be at risk and asks himself if this confirms something he already knew through prior communication with the student, or whether there is something uncharacteristic which has changed (such as a student who has been achieving suddenly showing poor predictions). For one (n=1) participant (P11) this is a particularly useful element of EAI. He also cross-matched the EAI data with student’s online information, for example, whether there is information from the Student Support Team which explains changes to student activity. Therefore, his use of EAI was described as holistic - using EAI data in conjunction with other aspects of student information platforms:

‘I tend to use this quite holistically. So, although we’re talking about early alert indicators here. One of the first places I’ll probably go from that point is just to go and have a quick look at the student’s contact record to make sure there’s nothing on there that you know if they’ve called student support and they said they’re having a crisis or something. So, I do tend to use it in a holistic way rather than just using it as a tool on its own.’ (P11).

Two (n=2) participants (P08, P11) also use the flags at the side of each student which indicate if there has been a significant change since the previous week. For example, if a flag was green last week and is now red, this is suggesting less activity than previous weeks (Figure 24).

‘I can just quickly scan the flags on the left-hand side of each student and if I see one that appears as a red downward arrow, I am immediately alerted that the student might be at risk, so it prompts me to look at the individual student data and take action if necessary.’ (P08).

Both these participants were the only participants who looked at the selection columns and selected the last log in date. From here they were able to get a quick view of whether a student had logged in recently and if not, they could check the individual student data. Both participants said this was particularly useful to identify students who were doing well but then dipped in their activity, as these are often the students who can be missed without the EAI dashboard. It would be difficult to predict this without the data if the student did not ask for help. Both participants stated that this was a quick way of getting an overall idea of student groups’ activity without looking at the entire dashboard.

5.4.3 Individual Student on Page 2

For this area, all participants looked at the individual student data and all stated that the most useful data was the VLE activity and the number of clicks a student made as this is most likely to inform ALs of the likelihood of the student being active on the module.

What was different to the participants in the eye-tracking study was that three (n=3) participants (P07, P08, P09) said that they looked at the prediction to see if there was a pattern emerging.

‘When I look at the short-term predictions, it’s clear straightway if there are any changes. I find that useful to get a clear visual. If the traffic lights are all green, I feel reassured but sometimes I see all green and suddenly a red. Now that’s a
worry. On the other hand, if I see a green among red, I feel reassured that the student might still be engaged.’ (P08).

Two (n=2) participants (P09, P10) stated that they did not see this as useful as it was historical data rather than predictive (e.g., it was information that they already knew so it did not tell them anything they did not already know). This was not an area that any of the participants in the eye-tracking observation focused on although it was included as an AOI.

Long-term predictions were the least viewed AOI and there was some uncertainty as to their relevance. For example, one (n=1) participant (P10) was confused about the percentage likelihood of completion, conflating them with percentages linked to assignment scores. Another participant (P09) did not know what the abbreviation FLP (fee liability point) meant so tended not to use them.

5.5 Discussion of Findings from Eye-Tracking and Screen-Sharing

By observing how participants use the EAI dashboard the evidence from this chapter has taken the discussion beyond self-reports to develop a fine-grained understanding of actual use which was not apparent from the semi-structured interview findings in Chapter Four. Using a convergence approach (discussed in Chapter Three Section 3.8.2), the following section discusses the combined findings from Study One and Study Two.

5.5.1 VLE Page 1

From the eye-tracking observations and the metrics applied, participants spent the most overall time looking at the VLE Page 1 AOI. Yet from the RTAP interviews participants stated that they did not find it particularly useful to their role as teachers as it was not specific to their tutor group. Most of the time spent on this AOI was reported as being re-familiarisation with the EAI visualisations, particularly for infrequent users and who need a reminder of the dashboard functions. Some participants were interested in seeing the bigger picture of how the entire cohort of students performed on the module, but this was more out of interest than functionality. Similar findings applied to the screen-sharing observation where CTAP interviews (without the metrics) showed that the most time spent here was to re-familiarise with the dashboard. One screen-share participant who had had no previous training, or management support and had only just started using the EAI dashboard spent the most time looking at this AOI where the more regular users across both eye-tracking and screen-sharing tended to spend less time and moved quickly to the tutor group AOI.

5.5.2 Tutor Group Page 1

Using eye-tracking observations and RTAP interviews showed that the tutor group AOI was viewed by all participants to identify students most at risk of not submitting their TMA. This was also true in the screen-sharing and CTAP observations. The focus of attention was primarily on the short-term prediction and particularly the traffic lights for each student
which indicate whether a student is likely to submit their next TMA. The overriding reason given for interest in this area was that it was an area which they felt they had some control over as they could influence the outcome as to whether the student submitted their next TMA (or not) by making timely contact with them and making referrals for additional student support services if necessary.

Some participants looked at the short-term prediction indicators which briefly explain the reason for the prediction (such as whether it is based on VLE activity previous TMA submission or demographic information such as occupation) and were able to demonstrate understanding of these. Some of the prediction indicators were not clear to participants, for example where summary activity for a student’s engagement was used as an indicator, other participants were confused as to whether this was a positive or negative indicator of risk. Other participants identified that the blue bar indicators were a clear percentage of risk (the longer the blue bar the greater the risk of non-submission). Therefore, it would be recommended that the prediction indicators were clearer to all users by improving the wording for example what relevance is occupation to whether the student will or will not submit.

Less attention was given to the long-term predictions which were not considered as useful as they are only updated four times throughout the module rather than weekly as is the case for short-term predictions. Participants reported that they did not feel that this was particularly useful and in some cases the participants did not understand the data or conflated the percentages with TMA scores.

Addressing the selection of columns option, the participants who used the selection columns were able to access more specific data such as being able to see the last log in date. They could also remove data which they did not find useful such as the staff tutor identification. For those participants who used these functions the RTAP interviews lead to more nuanced detail about how they might support a struggling student which thus indicated that understanding data was influential on the potential outcomes for students.

5.5.3 Individual Student Page 2

The observation of the VLE activity of the individual student was viewed for the longest time. However, unlike the VLE on page 1, RTAP and CTAP identified that the length of time on this AOI was because it was the VLE activity of individual students, that participants found most useful.

Of the nine participants who viewed this page (four (n=4) from the eye tracking study and five (n=5) from the screen-sharing study) multiple students were observed in the eye-tracking observation (Table 8). In the screen-sharing, only Student C (who was at risk of non-submission) was chosen by all participants. The eye-tracking study identified one participant who did not think Student C was still active on their studies so did not look at
their data. This finding suggests that students at risk of fail or non-submission are the main focus of attention for intervention. However, the fact that one participant did not look at it at all showed that there is also a position taken that despite having the predictive data there are some teachers who hold the belief that some students cannot be 'saved'. From the RTAP eye-tracking interview however it was evident that this was not so much an unwillingness to intervene, but more a resigned approach based on the basis that some students don’t participate after registration. This participant felt that time could be spent looking at those students who are struggling but active. The three other eye-tracking participants who looked at Student C stated that they were surprised by the data and had expected that they would not be able to offer meaningful support, but on examination of the individual data they were able to suggest actions. Two of the participants noted that an extension was recorded so the student was in contact with their tutor. One participant had not been aware that the option to see a recorded extension was available.

Expectations were that participants would find the individual student’s short-term predictions more useful than their long-term predictions. Table 8 showed that for the eye-tracking observation, the short-term prediction data was viewed more than the long-term predictions across the students viewed. RTAP interviews identified that long-term predictions were not as useful to participants and Table 8 showed that these predictions were viewed the least. However, as noted already, it is not possible based on data alone to assume that length of time observing an AOI is an indicator of higher interest without looking also at the RTAP and CTAP interviews. In this instance the interviews did confirm that expectations were met. From both RTAP and CTAP interviews, it was identified that participants felt that they could influence short term outcomes through engagement with a student, so they were more likely to use these, in favour of the long-term prediction indicators.

The following section outlines the main emerging themes that were observed from the combined eye-tracking and screen-sharing studies.

### 5.5.4 Emerging Themes

**VLE:** Two of the eye-tracking participants conflated the meaning of the VLE graph on page 1. One participant thought it measured their tutor group against the average student across the overall cohort and the other reported that it showed their individual student data as measured against the overall cohort.

**Tutor group Page One:** Two participants did not use the function to progress to page 2 to see individual data despite this being seen by all other participants as the most useful function of EAI. These participants had not attended a training session so had worked out the functions themselves. Both reported they were confident in the use of technology and used data in their everyday life. Three participants across both the eye-tracking and screen-sharing observations did not understand the function of the blue bar short term prediction...
prediction percentages and stated that they did not use these as they found it confusing. One participant had just become a recent user of EAI and stated he needed time to 'play' with dashboard to fully understand its function. There was also confusion about the prediction indicators which were too brief in their explanation to be useful.

**Long Term Predictions:** RTAP interviews from the eye-tracking showed that there was confusion about the function of the long-term predictions and some conflation between the long-term percentages of the likelihood of completion and passing the module with what some participants thought was a predicted overall grade on completion of the module. RTAP and CTAP Interviews also showed that the term FLP (fee liability point) was not clearly understood and its relevance to the data was not clear.

**Selecting columns:** Six participants across both studies did not use the option to change the data they could see by selecting columns which would give them more information. None of these participants had attended a training session

**Individual Student AOI Short Term Predictions TMA predictions and Scores:** Overall participants showed awareness of this function but in both the eye-tracking and screen-sharing observations, there was confusion about the meaning of the prediction summary due to its brevity and potential for misunderstanding.

Even though there was misunderstanding as to how the EAI dashboard functions worked, and in some cases not recognising that some functions were available, this needs to be seen within the context of EAI being an additional teaching tool and only part of the picture. Some teachers will have their own ways of understanding student behaviours (as discussed in Chapter One Section 1.2) However, using it to its full potential has benefits for student support and success that could otherwise not be achieved. EAI is identified in this research as a positive tool to aid teachers, yet it can be seen from this research that positive outcomes can still happen when the full range of functions are not necessarily used.

### 5.6 Conclusion

The findings from Study Two and Study Three have identified that participants had different levels of engagement according to their experience. Moreover, when converging these findings with their self-report (Chapter Four) both confidence in using technology and data literacy skills were reported as high in confidence by all participants. However, from the observations and metric measures in the two studies in this chapter we observe that there are still errors of data interpretation when using the EAI dashboard (Theme 1). Whilst this can in part be attributed to the individual participant’s skill level, it also needs to be seen within the context of the support available to adopt use of EAI (Theme 2) particularly in the context of available training and the acceptance of the organisation to support the use of EAI. Further, in terms of usefulness (Theme 4) there are implications
identified from the observations insofar as participants not being aware of the full range of functions which in turn has the propensity to limit the support offered to students. Using observation and eye-tracking has uncovered a depth of understanding that would not be obtained by self-reports alone as it demonstrates that there are differences between participants’ perceptions and their actual use (Theme 1). One of the shortcomings was that information from the screen-sharing did not give the same level of detail and nor was it possible to track the trajectory in the same way as it was with eye-tracking as there was no way of using metrics to get a finer grained observation of use.

Chapter Six continues this discussion by addressing the implications of this research, ways of developing a theoretical model which is more specific in explaining PLA use. It reports on the limitations of the research and ways in which this research can inform future practice.
Chapter 6 Conclusion

6.1 Introduction

This research takes the position that the use of Predictive Learning Analytics (PLA) can make a difference to teachers in how they support students studying at distance. Throughout this study I have aimed to engage reflexively with the literature, the data, and the research process. Reflecting and recording my responses has enabled me to work simultaneously on examining the literature whilst being mindful of my own experience as an Associate Lecturer (AL), a user of PLA, and a researcher.

This chapter now draws the research together by clarifying how the three studies carried out have identified where change is needed to support the use of PLA for teachers in Higher Education Institutions (HEIs) working at distance by addressing following research questions (RQs):

| 1) How do existing teacher beliefs influence Associate Lecturers’ use of PLA? |
| 2) How does knowledge of (a) technology and (b) data literacy relate to Associate Lecturers’ use of PLA? |
| 3) What are Associate Lecturers’ (a) perceptions of the use and usability of PLA and (b) actual use as measured by fine-grained eye-tracking approaches and observation of use? |

Section 6.2 is a discussion of the overall findings and their implications from the literature review (Chapter Two) and the data findings (Chapters Four and Five). From here Section 6.3 outlines the original contribution of this research. Section 6.4 then moves forward to discuss the limitations this study and future directions of this research before moving forward to Section 6.5 which looks at how this research is relevant to professional practice with recommendations for changes to how we move forward in the light of the study findings. In Section 6.6 I conclude by reflecting on this research journey.

6.2 Addressing RQs

This journey has been an investigation into what might help teachers’ acceptance of PLA by examining the experiences of ALs using the Early Alert Indicators (EAI) dashboard at the Open University (OU). As identified by several authors in the literature review (Dourado et al., 2021; Ifenthaler et al., 2016; Herodotou et al., 2020a; Munzner, 2014; Herodotou et al., 2017; Herodotou et al., 2019; Herodotou et al., 2020a; van Leeuwen 2015; Kaliisa et al., 2021), studies into PLA adoption are still in their infancy and more work needs to be done to understand what the barriers are and what can be done to encourage adoption (Chapter Two Section 2.3). This research has built on this stream of work to develop a fine-grained understanding of the use of EAI.
6.2.1 RQ1 How do Existing Teacher Beliefs Influence Associate Lecturers’ use of PLA?

In Chapter One we met Daisy and Pilar. Both Associate Lecturers (ALs) with different beliefs about the use of PLA. Daisy found PLA useful, but Pilar was sceptical which is not unusual in PLA adoption (Kaliisa et al. (2021)). Further it was identified that teachers who held positive attitudes towards technology in general are more likely to look favourably on its use than teachers who do not share this belief (Chein, Wu, and Hsu, 2014). However, adoption of a new system can be challenging as identified below.

Chapter One discussed the implication of the organisational structure (Kotter and Schlesinger, 1979; Dent and Goldberg, 1999; Piderit, 2000; Armenakis, et al., 1993). It was identified that how far an organisation is prepared to support the adoption of a new system is fundamental as to whether it is accepted by its end users. Further, the predominant perspective on resistance to change has tended to be from the organisational position and not specifically focused on individuals who are affected. This cannot be ignored insofar as the organisation’s role in supporting adoption has shown to have a fundamental influence on PLA adoption and more specifically for this research on the use of the EAI dashboard. Critiqued research on organisational change has shown that those who resist organisational change often do so with good intentions which are not always acknowledged (Piderit, 2000) (Chapter One Section 1.2). There is evidence that users of the EAI dashboard did not feel that the OU as an organisation fully supported the use of EAI. (Chapter Four Section 4.4).

Using Unified Theory of Acceptance and Use of Technology (UTAUT) as a model to structure responses, the determinant of facilitating conditions (FC) (Venkatesh et al., 2003) was not in place to support the adoption of EAI. However, the results of the interviews were mixed with some participants reporting that initially they were asked to use it but with no systematic continuation through support or training. From the perspective of the Theory of Planned Behaviour (TPB) (Ajzen, 1991) this model looks at whether the resources needed are available, whether a person holds the required skills and whether they are acting on their own indicators of intention. From this perspective whilst some participants did not always feel fully supported in systematically using EAI, for some this was not something that they would expect from their managers and felt that it was something that they should choose to do based on their own decision (particularly as there is no mandatory requirement to use it). In terms of support, this research indicated that peer support which is recognised as social influences (SI) in UTAUT (Venkatesh, 2003) was more useful in encouraging EAI use. Decisions whether to adopt the use of EAI were found to be based on ALs’ own volition rather by organisational instruction. Moreover, word of mouth among colleagues was seen as a positive form of support.
From the perspective of TPB, being faced with barriers can lead to less perceived control if those barriers are not within the individual's scope for change (Ajzen, 1991). Experience and confidence in using EAI meant participants were more able to overcome a perceived barrier provided it was something they had control over (such as developing an understanding of the data and navigating the dashboard and support from peers). However, there were some barriers which were beyond the control of participants (e.g., decisions outside of their capacity including lack of access to organisational support systems, access to training and for some users the faculty/module-wide decisions to restrict access to parts of the dashboard for some users). Those participants who had a positive belief towards the benefits of EAI were more likely to use it more effectively and systematically (Chapter Four Section 4.6).

When addressing issues of ethical use of PLA, studies showed that further work was needed to understand a significant area of concern for participants (Chapter Two Section 2.4). Using student data was a cause of concern for participants in this research along with the ethical implication that the knowledge of predictions might have on how ALs mark students’ work and whether seeing this information influences their marking decisions. Ethical use of data was thus a significant theme arising from the semi-structured interviews in Study One (Chapter 4 Section 4.8).

Often both stakeholders and students are not clear on the boundaries for the ethical use of data and there is a negativity towards the use of PLA despite the potential it holds to change the educational landscape based on ethical concerns (Drachsler and Greller, 2016; Roschelle, Lester, and Fusco, 2020) (Chapter Two Section 2.4). Although the intention of collection and use of student data for PLA use is ethically well intended (Cormack, 2016) from findings in this research it was evident that participants struggled with the ethical basis for using PLA, but this was also about the wider implications of using student data across the university (Chapter Four Section 4.9.7). It raises the question of whether we are ready to accept that using PLA data is a necessity in increasing support options for students. This research uncovered low engagement with ethical policies and guidance about use of PLA data. Participants were unsure how to broach with students that they had access to their PLA data even though there are clear ethical policy guidelines in place and students agree to sharing data for pedagogical good. However, more work is needed in the future to address this as the findings need to be viewed in the context of participants having not read the ethical guidelines for the use of PLA. Whilst studies discuss the importance of and ethical basis for the use of PLA, this is not considered as an indicator in any of the theoretical models.
6.2.2 RQ2 How Does Knowledge of (a) Technology and (b) Data Literacy Relate to Associate Lecturers’ use of PLA?

In relation to RQ2 the seminal theoretical models TPB (Ajzen, 1991), the Decomposed Theory of Planned Behaviour (DTPB) (Taylor and Todd, 1995) and UTAUT (Venkatesh et al., 2003) have been used to inform the research but it has been found that they are not sufficiently robust in their application to PLA to explain behavioural intention of the use of technology relating to PLA (Chapter Two Section 2.5).

Self-efficacy (TPB) was a strong indication of intention to use EAI, but what was also apparent from this research was that some participants had different perceptions of their abilities and their actual use. Data literacy skills were reported as adequate or high by all participants, but observation of use showed errors in understanding the EAI dashboard functions (Chapter 5 Section 5.5.4). Moreover, the fact that two participants were not aware of the ability to see individual student data was unexpected. From this it was concluded that self-reports do not always tell the whole picture and observing actual use leads to a clearer picture of use. As stated above however this cannot be seen entirely independently of other factors, for example the participants who did not look at the individual student data had not had training. Further, as stated by one participant (Chapter 4 Section 4.5) ALs are ‘time poor’ when it comes to having to make decisions about what is and is not important in their teaching roles.

There was acceptance by participants that EAI data was not always accurate and that circumstances beyond what is achievable identified using algorithmic information can occur (such as family crisis preventing student engagement in the module). This aligns with existing findings explaining errors in predictions by unanticipated events in the life of a student such as health and family issues and finance approval (Hoel and Chen, 2018; Hlosta et al., 2017 Hlosta et al., 2020; Kuzilek et al., 2015).

6.2.3 RQ3 What are Associate Lecturers’ (a) Perceptions of the Use and Usability of PLA and (b) Actual Use as Measured by Fine-grained Eye-tracking Approaches and Observation of use?

Fine-grained observation through eye-tracking and Retrospective Think Aloud Protocols (RTAP) interviews, was effective in identifying errors of EAI dashboard use with some further observation using screen-sharing and Concurrent Think Aloud Protocols (CTAP) interviews (Chapter Five).

Regarding the usefulness of EAI, there was evidence to suggest that the more the dashboard was used, the more useful it became to participants, who were then able to develop more nuanced use (such as also focusing on improving outcomes for more able students as well as those at risk of fail). Observations from Study Two and Study Three have shown that there are discrepancies between reported understanding of some of the EAI dashboard functions and actual use (Chapter Five Section 5.5.4). Participants who
were regular users of the dashboard were more likely to be able to mitigate algorithmic inaccuracies through their understanding of the parameters within which algorithms work and through developing familiarity with the dashboard. From this research there is a pattern emerging that there is no specific ‘type’ of EAI user however the common denominator was the desire to help students to achieve their study goal.

The following section looks at what original contribution this research has made towards understanding teachers’ use of PLA

6.3 Original Contribution

Even though research into teacher use of PLA is still in its early stages, there has been significant development in understanding its role in teacher-facing dashboards and supporting students which has been evidenced throughout this thesis. The following section addresses how I have built on the existing stream of work to develop my own position in this research by addressing new areas for development.

6.3.1 The Proposed Model of Technology and Data Acceptance in Education (PLA)

Two of the major gaps in all the models which have been identified as being of specific concern to teachers (Chapter Two Section 2.4) are the ethical concerns that they have access to student data that students themselves do not hold, and the trustworthiness of the PLA data. Ethical implications point to evidence that teachers are uncomfortable with whether students are aware of how their data is used and how far PLA data is accurate enough to be trustworthy. None of the theoretical models discussed in Chapter Two Section 2.5 include determinants specific to using PLA. Figure 27 is a proposed model to include the most relevant determinants from existing models along with the inclusion of ethical beliefs, trustworthiness of using predictive data, (e.g., reliance of algorithms) which are not incorporated in any existing model.

All the determinants of UTAUT (Chapter Two Section 2.5.3) were useful in informing the interview questions and was the model that was used the most to identify the themes in Study One (Chapter Four). However, from this research, gender did not influence the use of EAI and nor did age. Despite this, age is included in the model as it is identified as a limitation of this study due to the age demographic of participants (> 35). The emerging work of studies with students have indicated that younger students are less concerned about how data is collected and used (Rets et al., 2021). Therefore, if the age demographic of participants was younger (< 35) the results might have been different (discussed further in section 6.4 below).

From DTPB (Chapter Two Section 2.5.2) the level of self-efficacy held by participants was an indicator of likelihood to use EAI and from TPB the determinants of perceived behavioural control and attitudes towards a behaviour leading to behavioural use and the
degree to which a person views the behaviour as favourable or otherwise. (Chapter Two Section 2.5.1). This model also includes trustworthiness as a determinant as this was a finding from Study One (Chapter Four Section 4.9.7). Beliefs about the use of data for PLA was also identified as an issue and this also forms part of the proposed model.

Figure 27. The Proposed Model of Technology and Data Acceptance (PLA)

6.4 Limitations of the Study and Future Directions

The strengths of the study are that it has taken a holistic view of all the aspects of working with PLA and identified in detail each area of the dashboard what works, what doesn’t work, and how participants use it. Taking a fine-grained eye-tracking approach is a method which had not been carried out before. However, several areas have been identified which warrant discussion regarding limitations of the findings and outcomes of this research:

6.4.1 Participants

One of the limitations of the research was that it looks specifically at participants who had had some experience of using the EAI Dashboard at least once from those who were experienced users and had to use the dashboard for several years, to more recent adopters who were still developing their strategies for its use. It did not look at ALs who
did not use the dashboard at all.

The exclusion of participants who had not used the dashboard was based on a pragmatic decision. It would have been difficult to obtain the necessary data given that this research is an investigation of actual use of PLA to include an understanding of why despite using PLA, it is not well adopted. For example, whilst the semi-structured interview questions included generic questions about the use of technology and data, they also focused on specific aspects which depended on dashboard use. Further, because the research measures actual use of the EAI dashboard to gain a deeper understanding of the actions taken, participants who have not used the dashboard would not be able to demonstrate this in order to provide this insight. In future research it would therefore be useful to look at a cross-section of participants who actively made the decision not to use PLA at all and their rational, for example, the barriers preventing engagement: this thesis gives insight into perceptional barriers insofar as it identifies key themes such as how participants were influenced by the ethical implications of the use of student data. It also addresses participants’ concerns such as ALs already having significant understanding of students’ needs based on their teaching skills without the need for PLA. However, what is not known is what the barriers are that prevent teachers from engaging with PLA at all. Also, we do not know whether the perceptions that they hold are different to the participant sample for this research (e.g., those who have some experience of using PLA). Therefore, future studies could develop this line of inquiry.

6.4.2 Sample Size and Demographic Background

As discussed in Chapter Three Section 3.4 the sample size of the study was relatively small with only 11 (n=11) participants. Whilst no specific number of participants is required for qualitative research, Creswell (2015) has suggested that as guidance, for phenomenological research, a sample of ten is acceptable. In qualitative research rather than achieving generalisability (which is more associated with quantitative research) the objective is to make sense of and recognise the patterns among words to build up a meaningful picture without compromising the data (discussed in Chapter Three Section 3.7.2). Conversely, it has also been argued by Polit and Beck (2010) that whilst generalisability is predominantly the concern of qualitative research, there has been a move towards also considering generalisability in qualitative research as a way of providing evidence for findings.

For this research it was initially hoped that 15 ALs would participate, however with the limitations of travel to campus to participate in the eye-tracking study and the restrictions due to Covid-19, only 11 participants took part, but with a larger sample it might have been possible to capture more perspectives to allow for richer data and provide more evidence of the transferability and generalisability of this research within wider HEIs (see Section 6.4.3)
As a mixed methods study, quantitative data was also analysed through the eye tracking data of six (n=6) of the existing participants to address RQ3. The objective of quantitative research is to develop knowledge that applies to a wider population through the study of a sample from that population which is sufficiently large enough to prevent bias (Andrade, 2020). In this study the quantitative data measured the time spent on specific areas rather than gathering information from a wider population sample. The data was collected based on identification of areas of interest. However, in terms of generalisability the areas chosen would need to be based on the same criteria if repeated. Changes such as researcher decisions on how to choose areas of interest could result in different results.

The limited sample size alongside the requirement to have had some knowledge of using the EAI dashboard also meant that those who participated were likely to have some specific interest in using PLA particularly given that it is not mandatory to use it. To this end, their knowledge of PLA may not necessarily reflect that of other OU staff and/or the wider HEI community (discussed in Section 6.4.3) and specifically those people who have never used PLA at all (Section 6.3.1).

A further limitation was that only six (n=6) participants were able to take part in the eye-tracking and RTAP interviews. All participants had voiced their willingness to do a face-to-face interview using the eye-tracker but due to Covid-19 this was not possible. The screen-sharing option was an alternative option for observing those who were unable to participate in eye-tracking. However, the results of the screen-sharing did not give the depth of discussion or understanding that eye-tracking did. With more time it would also have been possible to measure more fixation data using eye-tracking albeit on a small sample. Again, this is an area for further development in future research.

The demographic information of participants placed them all in the age group of over 35 years. Perhaps millennial ALs might be very comfortable using PLA because they grew up with technology particularly given the determinants of UTAUT and in line with existing research there is evidence to suggest that younger age ranges are more comfortable with accepting how personal data is used (Chapter Section 2.4.1). This assertion is also supported by the findings of Rets et al. (2021) who found that younger students were more accepting of their data being used for learning analytics having grown up in the digital era (Chapter Two Section 2.4.1). Further, I understand how the adoption of PLA can challenge a teachers belief system.

6.4.3 Generalisability Across HE Institutions

This research has examined in detail the perceptions toward the use of PLA and measured its use to gain insights into how far perceptions and understanding are reflected in how the dashboard is used. The sample was taken from experienced ALs delivering teaching at distance. However, a limitation of this research is how far the findings would be transferable to other HEIs and particularly campus based face-to-face HEIs. Chapter
Three Section 3.2 outlines the unique setting of the OU as one of the only established UK universities to deliver online distance learning. From this research and from studies addressed in the literature review (Chapter Two Section 2.3) it is evident that individual HEI require PLA dashboards that meet their specific requirements. The EAI dashboard is designed specifically to meet the needs of students studying at distance. One of the generalisable aspects of this research is that particularly since COVID-19, there has been a move towards more online and blended learning modules and findings from this research is useful in informing ways in which they can encourage PLA use.

For other HEIs including campus-based, PLA has the propensity to provide additional insights to teachers in providing proactive support to students (Herodotou et al., 2021). Other universities have chosen to use their dashboards in different ways. For example, Nottingham Trent University (NTU) use PLA to identify at risk students (studying face-to-face) and how this correlated with a student’s socio-economic background. Unlike the EAI dashboard NTU did not use other demographics such as socioeconomic status or gender but relied exclusively on student engagement. Alerts for students with no engagement for 14 days were sent to the student’s tutor, they were asked to contact the student unless they knew of a reason not to. The ‘no engagement’ alerts successfully identified students who were at risk of both non-progression and achieving lower grades. The study recognised that students from socio-economically disadvantaged backgrounds were less likely to progress and achieve the highest grades. Over 75% of students from low socio-economic backgrounds progressed to the second year when identified via the PLA dashboard (Foster and Siddle, 2020).

The way in which NTU addresses PLA is different to the OU particularly in the collection of demographic information, therefore at first consideration this research would seem quite different and therefore not transferable. However, it has a role in informing the more generic aspects of PLA adoption such as understanding attitudes towards using PLA as a teaching tool, interpretation of dashboard functions, understanding and interpreting data and the importance of recognising when interpretations and understandings might be erroneous.

6.4.4 Institutional Barriers

Chapter One (Section 1.3) has examined issues of organisational change and its influences and the tendency to see change as the concern of the employee rather than the employer. Whilst this thesis has addressed the reasons for low adoption of PLA, a limitation is that it does not address the institutional barriers. However, the findings from the research indicates that this would be an area for further development. In research at the OU, Herodotou et al. (2019c) acknowledged the importance of the involvement of managers in the process of encouraging the adoption of the use of the EAI dashboard. Their findings indicated that the role management plays in providing the necessary
training and support influences how far teachers accept the use of PLA. This is not limited to the OU as similar findings have been in other institutions. Research by Sheikh et al. (2022) has shown that institutions with a strong leadership mandate and with clearly defined strategies in how PLA is used are more successful in implementing PLA effectively. They further argued that a positive culture of governance and decision making (e.g., where management adopt accountability and responsibility for data) is essential for using PLA effectively to provide the necessary insights into students’ learning needs.

To address this limitation, further research based on the findings of Theme 2 (Chapter Four Section 4.4) would be appropriate. For example, it was identified that participants believed that there was a lack of standardisation regarding how managers supported EAI use. These concerns ranged from managers who had no awareness of EAI, to initial support to use it which was not ongoing. There was, however, evidence of justifiable reason for this. For example, given the complexity of the various new systems in place, management prioritisation and the extent to which EAI was seen as a priority by managers. This meant that they needed to focus their support on other mandatory changes such as the core systems changes discussed in Chapter One (Section 1.3).

Research into these areas could include developing a better understanding of the hierarchical structure of the OU and its capacity to support EAI use. Findings from this thesis has found disparity in understanding of the use of PLA at different management levels and this could be further explored. A further area of investigation is the lack of funding for training and dashboard development as the funding stream for the use of EAI has been suspended. Understanding why there is a lack of recognition of the role of EAI from an organisational perspective is fundamental, as how we can expect teachers to be ready to use it if it is not supported from the top down.

6.5 Implications for Professional Practice

This research is part of a professional doctorate. In forward facing times with students increasingly working in blended and distance learning. PLA is a way to support students who might not otherwise be visible. Increasingly, HEIs are developing online modules or blended learning for their undergraduate and postgraduate programmes. Whilst this research has looked to support teachers working at distance at the OU, it will also inform those HEIs who are moving more towards a blended approach.

One example of the impact of this research so far is its contribution to the OU Strategy Plan (2021-2022) which has five initiatives: (i) Student Success: (ii) Excellent Teaching and Research: (iii) Growth and Sustainability: (iv) Dynamic and Inclusive Culture (v) Technology that Enables Success; in this initiative (v) the focus is on OU commitment to investing in technology that enables success, for example, investing in staff to recognise and maximise their contribution to using technology (Open University 2021).
This research has contributed to this initiative by identifying the need for more training and encouragement to use the EAI dashboard. Through engagement with the Strategy Team and AL Development Services, a team has been set up to deliver a short series of EAI briefing/training sessions specifically for AL colleagues to improve the uptake of the use of EAI. So far over 350 ALs have signed up to sessions and there is a waiting list for others who are interested.

Regarding the concerns of understanding the ethical basis for using EAI, a working group has been set up to update training and policy documents. Plans have been made to discuss with the developers re a ‘read me first’ banner on the dashboard signalling to people to read all policy guidance before using the dashboard.

Following the reports from participants of confusion around the understanding of the short-term prediction indicators: We have been able to hold conversations with the developers on how we might improve the wording of the prediction indicators to make the dashboard more understandable and discuss how these might be presented as a more useful visualisation.

6.6 Reflection of the Research Journey

Using PLA helps teachers to understand student behaviour, and identify students at risk, and this has been fully developed throughout this research both in the literature review the methodology and leading to the analysis. The research contributes to the professional role of educators in helping to form an understanding of the importance of using PLA as a tool to improve students’ outcomes and experiences to encourage and support teachers in supporting students.

My main teaching objective is to support students for whom education is not easy. The open access standpoint of the OU is a position I fully support being someone who has struggled with education and who entered higher education at a time when there was flexibility in entry criteria. Working as an AL I also came to understand how easy it is for struggling students to ‘disappear’ and not complete their studies.

OU students come to education from varied backgrounds and some with no qualifications (discussed in Chapter Three Section 3.3.2). My teaching objective is to support these students and encourage them to believe that education is indeed as much for them as it is for others.

In Chapter One Section 1.1 we met Daisy and Pilar and discussed the differences in their approach to supporting students. Like Pilar I initially felt scepticism in using PLA to support students as identified by Kaliisa et al. (2021). My journey took me from non-user to occasional user to someone who supports peers to use EAI. I was unsure how PLA could help me to help my students. From this position I can understand why some tutors
would be sceptical about its usefulness, particularly as it involves a change of mindset from using traditional teaching skills to adopting technology. Using PLA has been a journey of change for me, and one of the factors that help me to decide to adapt it as a regular part of my teaching practice, was recognising the need to know when a student might have disengaged. From experience working in a traditional university, it would have been expected of me to ensure that if a student did not attend lectures or seminars for any period of time, that I would investigate what are the reasons for this might be. Online distance learning is different as students manage their own attendance and engagement. It was by recognising that an early indicator of passive withdrawal or low engagement could help me to identify problems before they arose in the same way as I would do at a face-to-face university where I could visually see students in the classroom.

Having access to EAI has given me the opportunity to identify struggling students early enough to offer them the support needed for them to move forward and achieve their chosen qualification. I now have an opportunity to provide peer support to other ALs to do the same by providing briefing sessions. Carrying out this research has personally helped me to challenge my capabilities, push boundaries and move outside my teaching comfort zone with the knowledge that I am contributing to professional practice.
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Appendices

Appendix 1 – Delicate Checklist Drachsler and Greller (2016)
Appendix 2 Semi-Structured Interview Questions with Instructions

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</table>

Explaining the procedure to participants: Eye-tracking

Firstly, the screen needs to be calibrated and the participant must look very specifically at the screen avoiding head jerks or slumping and so may inadvertently move out of range while carrying out the task, which in turn risks interrupting the flow of the process. It is important to keep the eye focus within the screen parameters and keep the head movements as minimal as possible whilst making sure the participant is comfortable.

1. The use of the EAI dashboard:

It important to note that whilst ET provides a real time measure of the participant's processing and is largely a measure of natural behaviour it is only as good as the design and analysis of the study (Holmqvist, Nyström and Mulvey, 2012). Therefore, a strict criterion is applied to ensure consistency. After calibration, the screen will be ready set up with an anonymised example page of the EAI dashboard for a 2019J presentation and is set to week 14. All participants will see the same data on the screen and the eye-tracking process will take 3 minutes, during which their eye movements across the screen will be recorded. The purpose of the task will be for the participant to interact with the dashboard in the way that they normally would do when using it for the first time on a new module.

2. The playback of the process and discussion of decisions using retrospective think aloud protocols:

After the participant has looked at the dashboard, the recording will be played back showing the gaze plot of their eye movements across the dashboard which we will look at together using the following process:
Using RTAP, the participant will talk through the recording (slowed down to 50% of actual speed for ease of use). Using prompts participants will be asked at points for their rationale for the decision making as to where and where not to focus on the dashboard.

With the recording playing the following question will be addressed:

Looking at how you used the dashboard in this situation can you explain:

- What are you doing now? Please describe your process and your reasons for looking at X.

Prompts. Why did you click that item? What is it showing you? Why did you check that in particular? Is there a reason why you chose to look at X but not Y? Can you tell me more about that action? Can you take me through your rationale for taking that action?

(Note: Ask for clarification or to encourage the participant to make their response more concrete, specific, with examples, and whys).

3. Semi-structured interview questions:

(a) Technology use and data literacy

1. What technology do you use in everyday life?
   How would you describe your confidence in using technology in general? (Performance expectancy)

2. Do you feel more comfortable with specific technologies? Please explain.
   (Performance expectancy)

3. How confident would you say you are in reading/understanding graphs (such as bar charts or data Table)? (Performance expectancy)

(b) EAI Use, beliefs and attitudes about using predictive data

Please tell me about your actual use of the EAI dashboard:

1. When did you first use the EAI dashboard?

2. How long have you been using it?

3. What motivated you to use it? (Performance expectancy)

4. How did you first find out about the EAI dashboard? When you first heard about the EAI dashboard where did the information come from?

5. When you first used the EAI dashboard what was your impression? Has this changed? If yes how? Please explain (Effort expectancy/behavioural beliefs)

6. What were your initial impressions about its usefulness? (Behavioural beliefs)
7. How frequently do you check the data? Why do you not use it more/less? 
   (Effort expectancy)

8. Which actions do you choose? Why do you look at those actions and what do you hope to get from them?

9. Are there any areas of the dashboard that you do not look at and if so, why is that?

10. Since using the EAI dashboard have your strategies to support students changed? If yes how? Please explain. (Performance expectancy)

11. Are there any specific influences on why and how you use the EAI dashboard? (e.g., peer influences, directives from module teams). (Social influences)

12. What are your thoughts about using EAI to support students (e.g., ethical considerations, workload management, retention levels)? (Effort expectancy)

13. Are you familiar with the policy on the ethical use of student data for learning analytics? Do you have any concerns about the ethical position of using the EAI dashboard, is this related to data collection in general or just EAI?

14. How does the ability to see the predicted grade relate to your marking?

15. How do you typically respond to the data? Please talk me through the processes that you would go through with a student flagged as at risk of non-submission of their next TMA. (Effort expectancy)

16. Do you have any concerns or anxieties about using the EAI dashboard? If yes what are they? Please explain. (Performance expectancy)

(Note: Again, ask for clarification or to encourage the participant to make their response more concrete, specific, with examples, and whys).

How far are you encouraged by faculty/school/module team to use Early Alert Indicators?

1. What support have you received in how to use the EAI dashboard either at faculty school or module level? If you were supported, please explain the support you received. (Facilitating conditions/Normative beliefs)

2. Are you receiving ongoing support to use the EAI dashboard? (Facilitating conditions/Control beliefs/Self-efficacy)

3. Has either the faculty school or module team influenced your use of the EAI
dashboard and if so how? Please explain. (*Facilitating conditions*)

4. Did you receive any training about EAI? (*Facilitating conditions*)

5. Did you use the EAI support forums? Did you find them useful at all? (*Facilitating conditions*)

**Prompts.** Encourage development of discussion as to where the main support came from. Do you consider that as an organisation the OU is invested in using EAI? If yes, why do you think this? If no, why not? Should the expectation to use EAI be included in new contracts? Are there active discussions on your module tutor forum about using the EAI dashboard?

(Note: Ask for clarification or to encourage the participant to make their response more concrete, specific, with examples, but be aware that this might be contentious as there may be resistance to criticism of the organisation).

**Background information**

Additional questions if they are not covered elsewhere

1. What modules do you currently teach on?

2. What modules have you taught in the past?

3. What is your teaching experience (both with the OU and other institutions)?

4. How many years of teaching experience do you have?

5. Do you hold a teaching qualification?
Appendix 3 Information Sheet for Semi-Structured Interviews and Eye-Tracking

Participant information for the following study:

Teachers’ use of Predictive Learning Analytics: Experiences from The Open University UK

Anna Gillespie EdD Research Student/Associate Lecturer WELS, The Open University.

Aim of the study

This study is looking at the ways in which Associate Lecturers (ALS) use Predictive Learning Analytics (PLA).

It is the main study of up to 28 ALs across different faculties and forms part of the research for the Doctorate in Education (EdD). The study will take place between 1st November 2019 and 1st January 2021.

The purpose of the study is to consider whether PLA is effective as a tool in supporting students to succeed on a module. It will consider whether PLA is more effective on some modules than others.

It will focus on the experiences of ALs who have used PLA (and particularly Early Alert Indicators) to include; how far experiences as an AL influence the use of PLA; whether the faculty you are a part of influences how you use PLA; whether the design of the module play a part in how PLA is used. It will also look at whether managerial support influences how ALs use PLA.

As part of the study, I am carrying out an eye-tracking exercise using think aloud protocols; this will be a face-to-face interview whilst the participant is actively engaging with the EAI dashboard in the eye-tracking lab at the Jennie Lee Building Open University campus. It is envisaged that the exercise and think aloud interview will take around 30 minutes.

The eye tracker identifies which Sections of EAI dashboard attract more interest using heatmaps and gaze plots which can then form a discussion on why these Sections are the most used and why.

More information on eye-tracking is available at http://www.open.ac.uk/about/campus/jennie-lee-research-labs/our-services/eye-tracking-services

If you would be interested in participating in this, particularly if you are based on campus or if you are visiting campus for any other reason, I can arrange to book a lab and meet you there.

While I would really appreciate your participation, it is entirely up to you to decide whether to take part.

Participant expectations

Meeting at the Jennie Lee Building on campus where we will use one of the computer labs which is set up with eye-tracking technology.

There will be an initial short questionnaire to gather some demographic information.
The computer will be set up with the eye tracker ready to view the EAI dashboard. There will be a short calibration set up to complete which takes a couple of minutes just to make sure the equipment is ready. Once calibrated, you will be asked to spend approximately 5 minutes demonstrating how you use the EAI dashboard, using an anonymised student group. The eye tracker will track and record your eye movements to show where you look on the dashboard during the exercise. Using retrospective thinking aloud protocols we will discuss the focus of your attention to gain an understanding of your use of EAI.

Once you have completed the exercise, we will jointly view the recording pausing at appropriate points to address decisions you made such as:

- Which aspects of the EAI dashboard you looked at most and why?
- Which aspects of the EAI dashboard you looked at least and why?
- Why you chose to look at certain areas of the EAI dashboard.
- Why you spent more time looking at certain areas of the EAI dashboard
- Which areas of the EAI Dashboard you did not look at and why?

Confidentiality and security

As outlined on the consent form: The eye-tracking interviews will be face-to-face on the Open University campus and eye-tracking data will be collected online and anonymised. The anonymised recordings will be deleted from the main computer and saved on an encrypted USB viewed only on a password protected laptop.

Participants will not be identifiable in any published materials. The research is completely voluntary, participants are at liberty to withdraw at any time without prejudice or negative consequences up to 30th November 2021. No participant information will be shared with any third parties (including within or outside of the OU) other than the study team (myself, supervisors and if necessary, examiners).

Further information is available from a.gillespie@open.ac.uk

If you have any queries about this research that I cannot answer satisfactorily, you can contact my supervisors:

christothea.herodotou@open.ac.uk
bart.rientes@open.ac.uk

Thank you
Informed Consent for: Teachers’ use of Predictive Learning Analytics: Experiences from The Open University UK

Anna Gillespie EdD Research Student/ Associate Lecturer WELS, The Open University.

Taking part in the study

I have read and understood the study information dated below. I have been able to ask questions about the study and my questions have been answered to my satisfaction.

(Please highlight your answer in bold)

Yes  No

I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time up until 30th November 2021 without having to give a reason.

(Please highlight your answer in bold)

Yes  No

I understand that taking part in the study involves a one-to-one face-to-face eye-tracking exercise and interview at the Jennie Lee building Open University campus lasting no longer than 30 minutes, to discuss individual experiences of using predictive learning analytics as part of the role of Associate Lecturer at the Open University. Participation is voluntary and withdraw can take place at any time without prejudice or negative consequences.

Data Collection and Analysis

- Information will be collected by carrying out eye-tracking interviews face-to-face at the Jennie Lee Building, The Open University Milton Keynes.
- Only participants in the study, and the study group (researcher, supervisors and where necessary examiners) will have access to anonymised data and I agree not to share this
with anyone else.

- Interviews will be recorded for data analysis purposes but will not be made visible to other participants or anyone other than the study group.

- Eye-tracking data will be deleted from the computer in the Jennie Lee Building and will be stored on an encrypted USB and analysed using a password protected computer and OU login

Consent

I agree to the collection of eye-tracking data and understand that collected data will only be available to the study group.

I understand that the eye-tracking data and recording will only be available to the study group.

Use of the information in the study

I understand that information I provide will be used in research for the above Doctorate in Education.

I understand that personal information collected about me that can identify me, will not be shared beyond the study team.

My data will be anonymised for data analysis, reporting and publications.

I understand that my recorded interviews will be anonymised and stored until 30th November 2021.

I have been given an information sheet explaining in the process

Future use and reuse of the information by others

I give permission for an anonymised version of the eye-tracking data that I provide to be deposited in a specialist data centre in the form of transcripts so that it can be used for future research and learning if necessary.

(Please highlight your answer in bold)

Yes  No

Signed (Participant)

Date

This research project has been reviewed by, and received a favourable opinion, from the OU Human Research Ethics Committee - HREC reference number: 2979
Appendix 5 Information Sheet for Semi-Structured Interviews and Screen-sharing

Participant information for the following study: Teachers’ use of Predictive Learning Analytics: Experiences from The Open University UK

Anna Gillespie EdD Research Student/Associate Lecturer WELS, The Open University.

Aim of the study

This study is designed to look at the ways in which Associate Lecturers (ALS) use Predictive Learning Analytics (PLA). It will focus on the experiences of ALs who have used PLA and particularly the Early Alert Indicators (EAI). Interviews will be online using either MS Teams or if preferred, Adobe Connect.

The purpose of the study is to consider whether PLA is effective as a tool in supporting Students to succeed on a module. It will consider whether PLA is more effective on some modules than others.

This information sheet relates to the main part of this study which is intended to involve up to 20 ALs across different faculties and forms part of the research for the Doctorate in Education (EdD). The study will take place between 1st October 2020 and 1st January 2021.

Participant expectations

The study comprises of two elements:

- An online semi-structured interview to discuss your experiences of using the EAI dashboard and some general questions about your use of data in general. This will last no more than 30 minutes. This includes asking you to share the following: demographic information:
  - Length of time working in education
  - Length of time working with the Open University
  - Faculty worked in
  - Modules taught

  This will be followed by more structured questions to look at:
  - How far your experiences as an AL influence the use of PLA
  - Whether the faculty you are a part of influences how you use PLA
  - Whether the design of the module plays a part in how PLA is used.
  - Whether managerial support influences how ALs use PLA.

- An online screen-sharing exercise to ascertain how you use the EAI dashboard this will take no more than 30 minutes.
  - I will share with you an anonymised version of the EAI dashboard
  - I will ask you to spend approximately 5 minutes demonstrating how you use the dashboard when using your own tutor group.
  - In a replay of the recording using retrospective thinking aloud protocols (feedback of your experience of the exercise with some prompting questions from me) we will

Prior to Covid-19, this study was conducted by carrying out face to face interviews at the Jennie Lee Building, but this is now not possible. This revised information sheet is to reflect an alternative method of data collection (screen-sharing the EAI dashboard online). If you have been given the information sheet in relation to the face to face Eye-tracking study this now replaces it
discuss the focus of your attention to gain an understanding of your use of EAI.

While I would really appreciate your participation, it is entirely up to you to decide whether to take part. Where possible both elements of the research will be conducted at the same time (Taking no more than 60 minutes in total). However, this is not essential if two shorter interviews would be preferred.

**Data Collection**

Recordings of the screen-share will be deleted once data are collected and analysed and no later than 30th November 2021.

For transcription purposes the MP4 video recordings will be converted to MP3 audio recordings and then transcribed as a way of anonymising the data you provide.

All recordings (audio and visual) will be stored safely on an encrypted USB and accessed via a password protected computer and deleted no later than 30th November 2021.

Using MS Teams allows me to give you control of my screen, so you do not need to screen share from your own computer.

Using Adobe Connect participant names can be removed at source.

**Confidentiality and security**

The research is completely voluntary, participants are at liberty to withdraw at any time without prejudice or negative consequences up to 30th November 2021. Participants will not be identifiable in any published materials as all materials will be anonymised.

Participant information will not be shared with any third parties (including within or outside of the OU) other than anonymised data which may be shared with supervisors and if necessary, examiners.

Further information is available from a.gillespie@open.ac.uk

If you have any queries about this research that I cannot answer satisfactorily, you can contact my supervisors:

christothea.herodotou@open.ac.uk
bart.rientes@open.ac.uk
Appendix 6 Consent Form for Semi-Structured Interviews and Screen-sharing

Human Research Ethics Committee Consent for Participants.

Informed Consent for: Teachers’ use of Predictive Learning Analytics: Experiences from The Open University UK

Anna Gillespie EdD Research Student/ Associate Lecturer WELS, The Open University.

Please use an X to confirm agreement to the following statements:

<table>
<thead>
<tr>
<th>Statement</th>
<th>X</th>
</tr>
</thead>
<tbody>
<tr>
<td>I have read and understood the study information on the participant information sheet.</td>
<td></td>
</tr>
<tr>
<td>I understand that information I provide will be used in research for the above Doctorate in Education.</td>
<td></td>
</tr>
<tr>
<td>I have been able to ask questions about the study and my questions have been answered to my satisfaction.</td>
<td></td>
</tr>
<tr>
<td>I understand that taking part in the study involves a one-to-one online (video) screen-sharing exercise and an online (audio) semi-structured interview as outlined on the participant information sheet.</td>
<td></td>
</tr>
<tr>
<td>I agree to the collection of data as outlined in the participant information sheet and understand how my data will be anonymised and stored. Data will be anonymised for data analysis, reporting and publications.</td>
<td></td>
</tr>
<tr>
<td>I give permission for an anonymised version of the written transcribed account of the data that I provide to be deposited in a specialist data centre so that it can be used for future research and learning if necessary.</td>
<td></td>
</tr>
<tr>
<td>I understand that all audio and visual materials will be deleted as outlined in the participant information sheet no later than 30th November 2021 and that this will therefore not be deposited in a specialist data centre.</td>
<td></td>
</tr>
</tbody>
</table>
I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time up until 30th November 2021 without having to give a reason. Participation is voluntary and withdraw can take place at any time without prejudice or negative consequences.

Signed

Date